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Analytics in Maritime Weather Routing

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Abstract

Maritime weather routing for ocean-going vessels is a complex and time-consuming task due to the volume and diversity of required data as well as the intricate interactions between weather conditions and vessel characteristics. True North Marine (TNM), a Canadian consulting firm specializing in voyage planning for bulk carriers, supports hundreds of vessels daily through manual route planning performed by approximately forty planners. Increasing regulatory pressures, evolving industry best practices, more extreme and likely frequent events that impact "traditional" weather patterns that in turn impact voyage planning. and growing variability in vessel strategies for fuel use, voyage duration, and safety have made traditional planning methods increasingly inadequate.

To address these challenges, TNM has developed a decision support system (DSS) called OptiNav AI, which incorporates descriptive, diagnostic, and prescriptive analytics. The DSS uses vessel characteristics such as dimensions, engine specifications, and calm-water performance curves along with historical and forecasted weather data. Machine-learning tools are applied to identify relationships between fuel consumption, speed, and environmental conditions, whereas expert knowledge from experienced planners and ship captains is embedded to ensure operational realism. Weather forecasts provide detailed three-hour wind, wave, and current predictions for seven days, forming the basis for minimum-cost routing optimization on a discretized spatial network of navigable ocean. A three-step approach determines the overall route structure, refines the structure with forecast-specific adjustments, and computes an optimal speed profile. Given the large scale of time-expanded spatial networks, several customized preprocessing steps are used to maintain computational efficiency.

OptiNav AI has been operational at TNM and among major clients since late 2022, delivering significant performance gains. Field results indicate average fuel savings of approximately 3.5%, equivalent to 1–1.5 metric tons of fuel saved per bulk carrier per day. When scaled to fleets of several hundred vessels, the economic and environmental benefits are substantial. OptiNav AI represents a major step toward data-driven, environmentally aligned, and operationally efficient maritime voyage planning.

Keywords: Weather routing; Maritime transport; Uncertainty; Multi-objective, Decision support system.

Problem Description

Maritime Transport

Maritime transport is a critical component of global commerce, accounting for more than 80% of intercontinental freight movement. Although vessels operate across all major oceans, certain corridors are used far more intensively. Data collected by the International Monetary Fund between January 2015 and February 2021 of hourly automatic identification system (AIS) positions of commercial vessels illustrates the main route arteries (Figure 1) across the oceans. Maritime transport remains one of the world's most significant contributors to air pollution, as large ocean-going vessels traditionally consume substantial volumes of high-sulphur fuel. As a result, the maritime industry faces strong international pressure to reduce its atmospheric emissions.

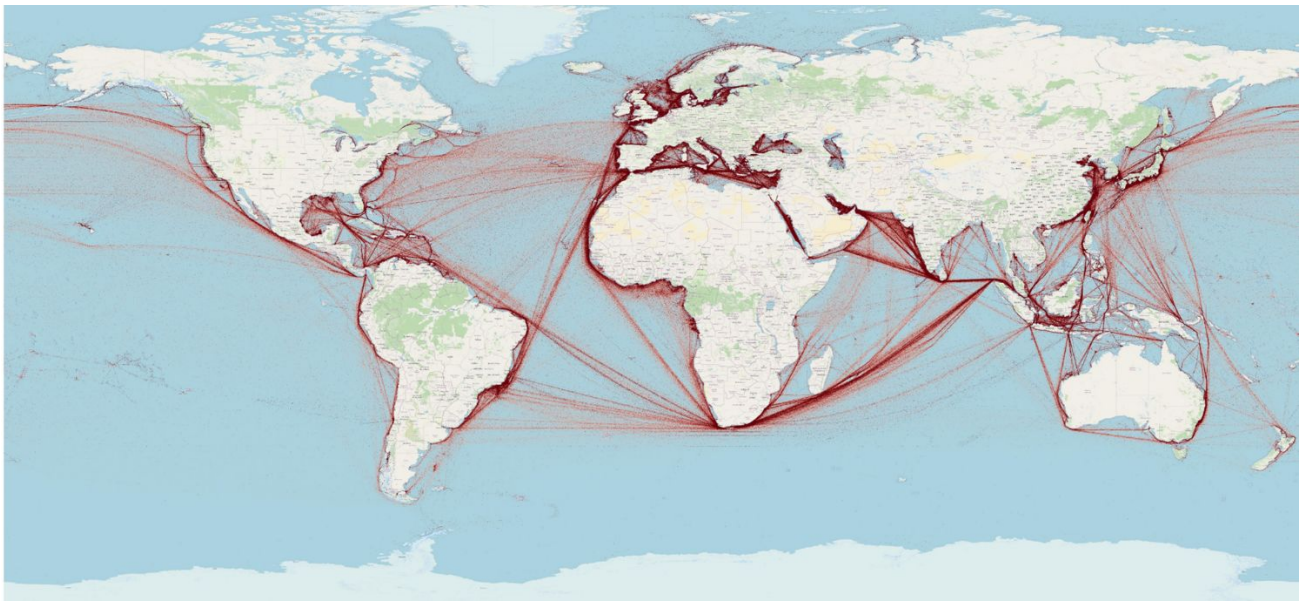

Figure 1. The main maritime route arteries across the oceans. Public data collected and available at International Monetary Fund databank. Illustration made with QGIS and background map from OpenStreetMap.

In April 2018, the International Maritime Organization (IMO) adopted an initial strategy aimed at limiting greenhouse gas (GHG) emissions from vessels (Joung et al., 2020). This strategy establishes two primary targets: a reduction of at least 40% in CO_2 emissions per transport activity by 2030 compared with 2008 levels and a reduction of at least 50% in total annual GHG emissions by 2050. Complementing this effort, the IMO introduced a major regulatory change in January 2020 by lowering the permissible sulphur content in marine fuel from 3.5% to 0.5%, with an even stricter limit from 1.0% to 0.1% in designated Emission Control Areas (ECAs) (Čampara et al., 2018), as illustrated in Figure 2. Before January 2010, the limit in the designated ECA zones was 1.5%, and the general limit was 4.5% before January 2012.

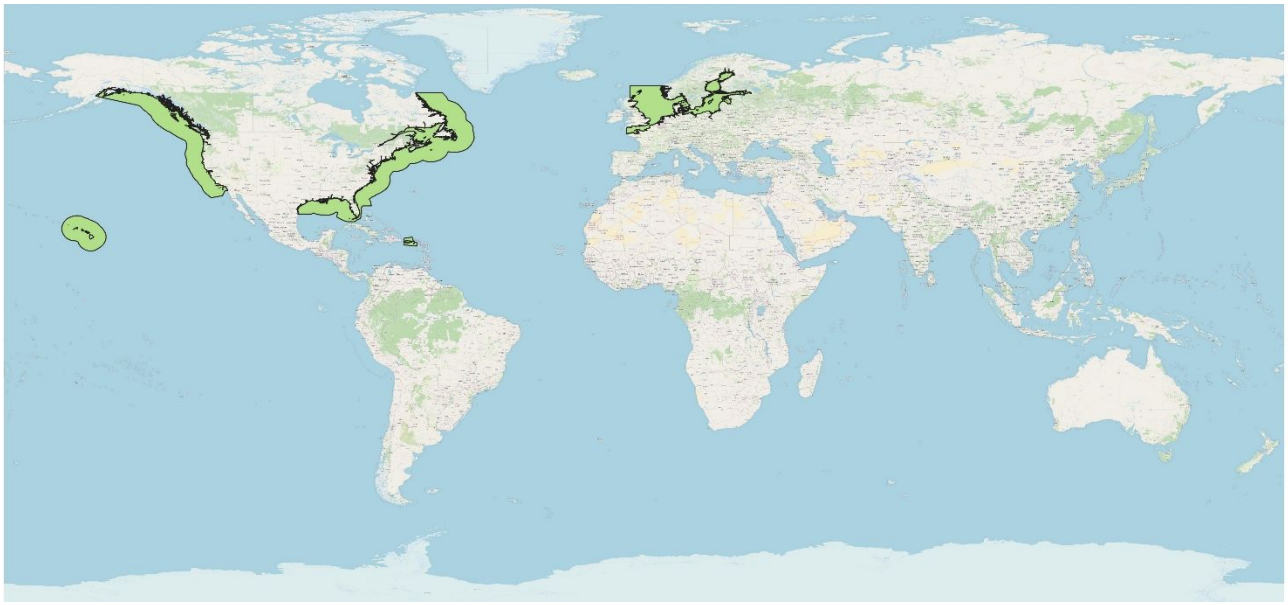

Figure 2. Dedicated ECA zones (green) that have a maximum limit of 0.1% sulphur content. Zone limits are defined in MARPOL Annex VI. Illustration made with QGIS and background map from OpenStreetMap.

These regulatory measures have far-reaching economic and operational implications for the shipping industry (Pereira, 2025; Sigalas, 2022). The shift to low-sulphur fuels increases fuel costs, as 0.5% sulphur fuels compete with other high demand fractions in refinery outputs. Consequently, traditional routing strategies that prioritized shortest voyage duration are giving way to approaches that emphasize fuel efficiency or a hybrid balance between time and cost. Such changes further underscore the need for advanced optimization tools and performance-oriented voyage planning to help ship operators comply with evolving environmental standards while maintaining competitiveness (Chen et al., 2025).

True North Marine

TNM is a Montreal-based company that provides voyage routing advice and weather forecasting services to ocean-going vessels worldwide. Its services are primarily used by multinational trading houses that charter vessels to transport bulk commodities across global markets. TNM operates four planning centres around the world, enabling 24/7 support. Each day, more than 700 vessels are assisted by approximately 40 route planners who determine the optimal route and speed based on prevailing and forecasted weather conditions. To support these operations, TNM collects extensive data on forecasted weather patterns, vessel performance, and global trade flows. The TNM business model is founded on the principle that systematically integrating these data sources with experienced planners enhances the efficiency of voyage planning and equips clients with information that improves operational and commercial decision-making. TNM core services include the preparation of an initial voyage plan between the departure and arrival ports, followed by daily updates as the voyage progresses. These updates account for revised weather forecasts, changes in vessel position, and other operational considerations, and are communicated directly to vessel captains and client representatives. Until recently, these route proposals were generated manually by experienced planners, drawing on their professional judgment and accumulated expertise.

Due to the higher cost of low-sulphur compliant fuels, the maritime transportation sector has been actively seeking solutions to reduce overall voyage costs. In 2019, TNM realized that the expected priority on routing would increase the time needed for planners. The overall assumption is that fuel consumption is more important and interacts more with the chartering cost that used to be the dominating priority. In practice, this means that planners must consider more route options that considerably increase complexity and in turn planning time. To understand what type of manual decision support can be developed into automatic decision support, TNM contacted researchers at the IVADO (ivado.ca) and CIRRELT (cirrelt.ca) research centres. In 2020, an R&D project was initiated among three universities in Quebec; this project was funded jointly by MITACS, Prompt, and TNM. TNM started an implementation project to develop the DSS OptiNav AI in 2022 motivated by the preliminary research results. This project provided TNM with advanced analytical tools to support planning activities and provided scientific contributions in the development of new detailed models and methods useful for weather-based vessel routing.

Manual Weather Routing

The primary task faced by TNM route planners is determining the optimal path between a vessel's current position (or departure port) and its intended arrival port. A route is defined by a sequence of waypoints and an associated estimated time of arrival (ETA). *Maritime weather routing* is a service provided by commercial companies for cargo vessels to optimize their voyage performance. Weather routing is inherently complex because vessel performance is highly sensitive to vessel-specific characteristics and weather conditions. Each vessel differs in length, engine type and power, beam, draft, surface area exposed to wind, and total tonnage. Moreover, each vessel has a calm-water resistance profile derived from early sea trials—conducted in either laden or ballast condition—that record fuel consumption at various speeds under ideal weather conditions. These trials do not account for performance under the variety or wide spectrum of real-world weather influences such as wind, waves, and currents. Vessel owners typically provide simplified performance estimates for different weather categories, but these values are often imprecise and may not reflect actual operational behaviour.

Over the years, TNM has accumulated extensive empirical data on vessel fuel consumption and corresponding weather conditions. This information is primarily collected through "noon reports" in which captains daily report, e.g., prevailing weather conditions and remaining fuel quantities. As a result, TNM possesses experience-based performance insights for many of the vessels it supports.

Detailed weather forecasts form a central component of the routing process. Forecasts provide three- or six-hour predictions of wind speed and direction, wave height and direction, and ocean currents up to seven days in advance. Additional information on severe weather events such as hurricanes, typhoons, or cyclones is also available, including expected track, size, intensity, and speed.

When a new route is planned, the planner begins by checking whether the voyage has been performed previously by the same vessel or by similar vessels. Historical routes are valuable starting points and can guide the initial choice of a preferred path. This preliminary route is loaded into the TNM Fleetview system developed by Papersoft Technologies in collaboration with TNM, providing visual and

quantitative weather representations along the route (Figure 3). Given the large number of previously planned voyages, planners often have access to several historical paths that can be used as initial candidates.

Fleetview plays a crucial role in supporting route analysis. The system overlays wind, wave, and current information along the proposed path, enabling planners to evaluate the operational environment and refine their recommendations. Experienced planners draw on their understanding of how specific vessels respond to various weather conditions and manually adjust the physical route and the speed profile between waypoints. The outputs of this process include an estimated time of arrival at the destination port and an estimate of expected fuel consumption and overall voyage cost. If a preferred ETA has been requested, the speed settings along the route are further adjusted to meet the required schedule.

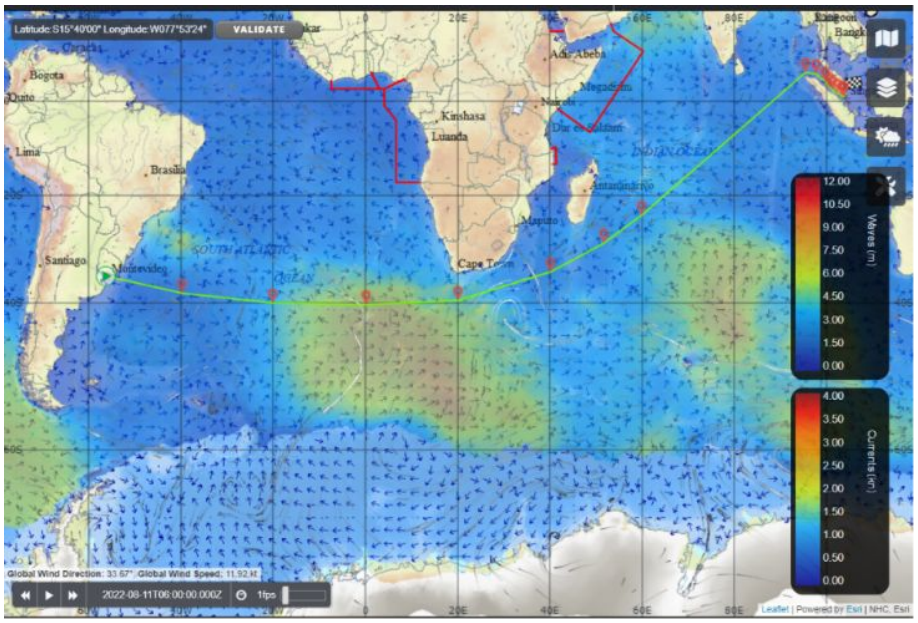

Figure 3. Screenshot of a route and network to represent a potential route between Buenos Aires and Singapore from the manual Fleetview planning tool (TNM developed system). The route is described with a set of waypoints and the current weather condition is visualized in a standardized form.

Challenges

In keeping with current TNM practice where route planning was performed manually, planners typically select the shortest safe-time route between departure and arrival ports. However, the growing emphasis on fuel efficiency and GHG emissions has substantially increased the number of factors that must be considered during voyage planning. This emphasis shift has also expanded the space of feasible routing alternatives that must be evaluated before selecting a proposed *optimal* solution. Such complexity exceeds manual planning capabilities, thereby necessitating the development of advanced analytical tools to support and systematize decision-making.

The transition from manual routing to data-driven optimization is not straightforward. As with any analytical system, output quality is fundamentally determined by input quality—echoing the well-known

"garbage in, garbage out" principle. Consequently, a central challenge of the project has been developing accurate performance functions for fuel consumption, route time, and safety. The most effective approach has been constructing a digital twin of each vessel, combining quantitative data with the experiential knowledge of TNM planners and vessel captains. This digital representation enables the system to better capture complex interactions between vessel characteristics, environmental conditions, and operational constraints.

Several categories of information are essential for this modelling. First, vessel-specific characteristics play a critical role. Each vessel has unique dimensions (length, beam, height, draft) and specific tonnage, engine configuration, wind-exposed surface area, and displacement. These parameters influence vessel behaviour in varying sea states. Although some vessels have "sister ships" with similar designs, performance varies enough that individualized modelling remains necessary.

Second, fuel consumption and route time depend on a complex interplay of factors, including weather conditions, in ballast or laden vessel, and the ship's hydrodynamic properties. Performance curves produced during delivery sea trials describe engine power, vessel speed, draft, and other factors under calm-water conditions but do not account for real-world weather variability. Additional factors such as hull fouling, propeller efficiency, and long-term degradation further affect performance. Over years of operation, TNM has collected a substantial dataset through captain daily reports, called "noon reports", documenting fuel use, speed, and corresponding weather conditions. These longitudinal empirical data have proven essential for refining consumption models.

Third, navigational limits impose additional constraints. Vessels must follow established channels that sometimes require pilots, such as in the Panama Canal or the Strait of Magellan, or to navigate busy chokepoints like Singapore in the Strait of Malacca (Figure 4). Some passages involve transit fees and potential queuing times, both of which must be incorporated into route evaluations. Vessels must also avoid shallow waters, islands, and restricted areas (e.g., oil and gas platforms, piracy areas, and military conflict zones). Furthermore, emissions regulations impose additional restrictions: within designated ECA (Figure 2), vessels must switch to lower-sulphur fuels, which affect cost and operational planning.

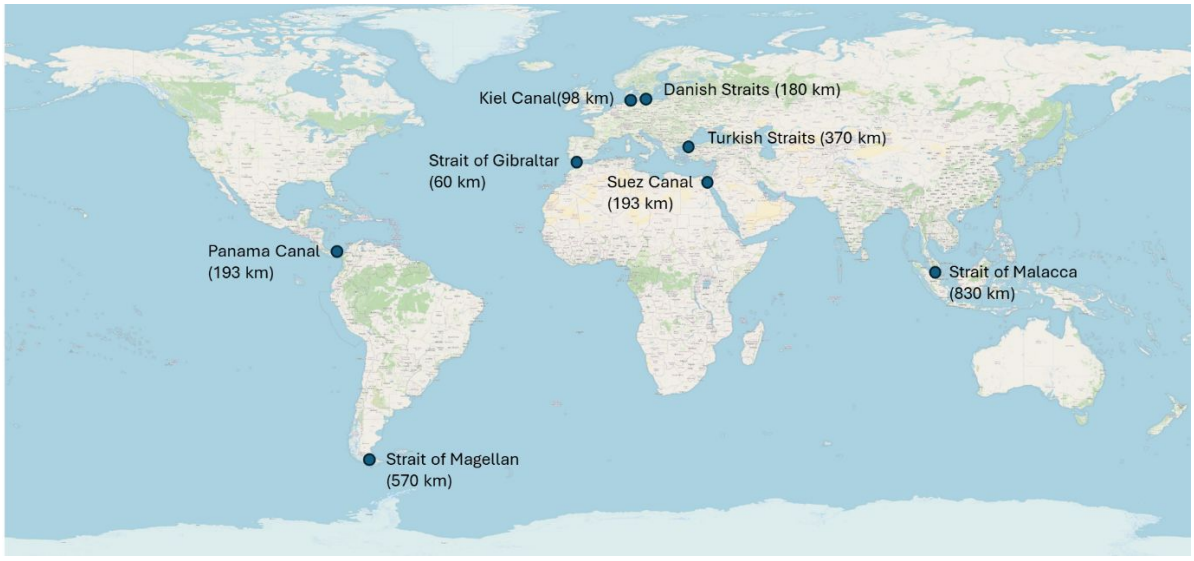

Figure 4. The main canals and straits (including their lengths, Wikipedia) where special consideration must be accounted for and may include required pilots. Illustration made with QGIS and background map from OpenStreetMap.

Fourth, multi-objective planning is essential, as the optimal route depends on the weighting of several potentially conflicting objectives. Operators may aim to minimize cost, reduce voyage duration, meet specific port arrival times, avoid delays, or mitigate risks, all while considering forecasted weather conditions. While fuel and time can be expressed in monetary terms, safety elements are often represented probabilistically or through strict thresholds (for example, avoiding areas with excessive wave heights or predicted hurricane activity). Lim et al. (2018) review maritime risk analysis models largely based on historical accident data, whereas Sharif et al. (2024) review safety risk approaches that emphasize weather-induced vessel responses.

Finally, big data management is a crucial component of any practical decision-support system. Because TNM operations span the globe with hundreds of supported vessels, the system must process vast amounts of heterogeneous data. Weather forecasts alone arrive every three hours and include substantial volumes of information on wind, waves, and currents. Navigational charts provide additional layers of data on islands, bathymetry, and other hazards. Efficient data handling is essential because route evaluation must be performed within seconds to support operational decision-making. The ability to manage, preprocess, and rapidly query these datasets is therefore fundamental to developing a robust and scalable optimization framework.

Analytics: Models and Methods

The developed DSS OptiNav AI is composed of multiple integrated modules (Figure 5). At the core of the system lies a large-scale network optimization engine designed to identify the minimum-cost route across an extensive time-expanded spatial network. Given the size and complexity of this network, computational efficiency is critical. It is therefore essential to accelerate all operations related to arc

feasibility, traversal time, and associated cost calculations. To achieve this, OptiNav AI incorporates several preprocessing modules that compute as much relevant information as possible in advance, enabling rapid network construction during real-time routing. Special procedures are also required for portions of the voyage that extend beyond the seven-day forecast window, as these segments cannot rely on detailed weather predictions and must instead use structural or historical information. The following sections describe these key modules in greater detail.

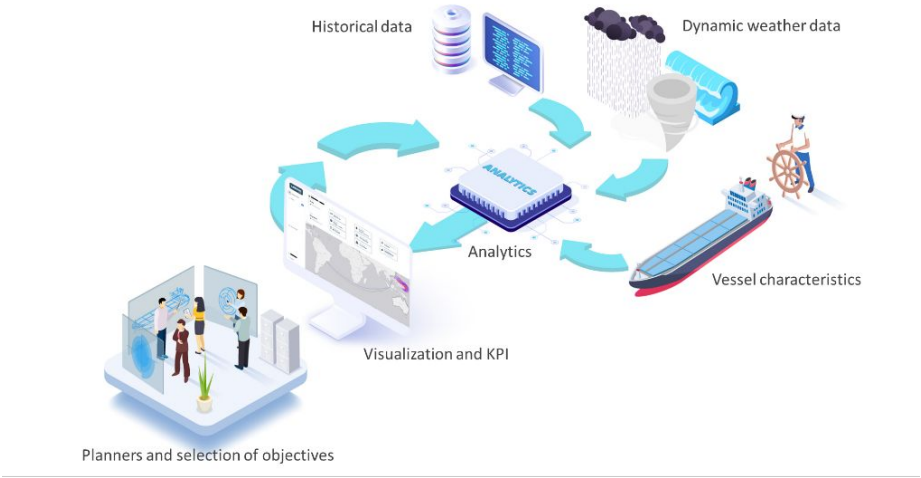

Figure 5. Illustration of the modules in decision support system OptiNav AI. Illustration by Maxime Houssin.

Data Available

Dynamic Weather Data

Dynamic weather information is one of the most critical inputs for maritime routing. Forecasts are available for up to 180 hours and are updated at three-, four-, or six-hour intervals depending on the data source. Wind fields are provided as speed values in two orthogonal directional components, and ocean currents are reported in an analogous two-component format (Figure 6). Additional meteorological variables, such as atmospheric pressure, are also included. These data are supplied by Frivind in Norway, which aggregates meteorological information from multiple international providers and compiles it into GRIdded Binary (GRIB) files, a standardized format widely used in meteorology and marine forecasting.

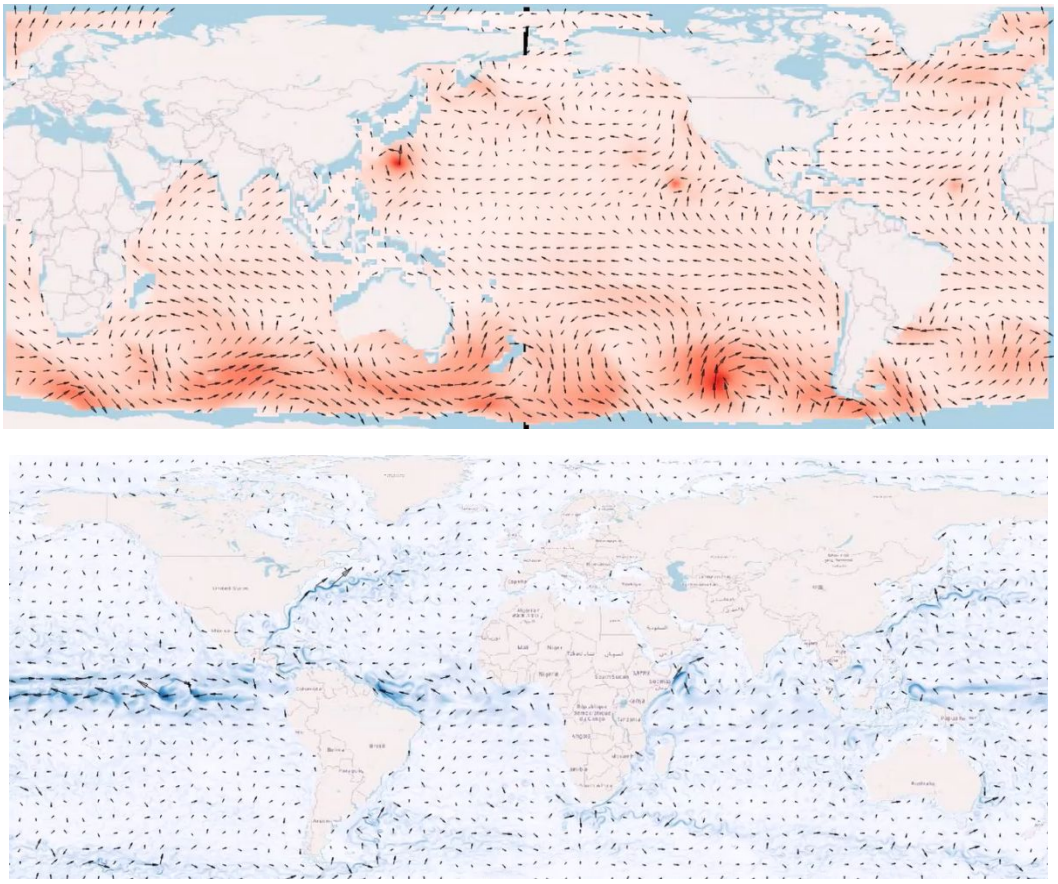

Figure 6. Illustration of forecasted wind information (top) and currents (bottom) for a particular time interval. Data is based on TNM historical weather forecast data (February 2021). Illustration made with QGIS and background map from OpenStreetMap.

The weather data are available at various spatial resolutions. As illustrated in Figure 7, wind, wave height, and wave period are provided on a raster of approximately 127 km × 110 km (corresponding to 1.25° × 1.0°), whereas current data are available at a much finer resolution of approximately 8.3 km × 8.3 km. Because a single network arc typically represents roughly eight hours of sailing time, each arc traverses numerous raster cells. A central computational challenge lies in accurately and efficiently evaluating weather conditions along each arc, particularly given the very large number of arcs in the network. To address this, weather datasets are preprocessed and structured to ensure environmental information along any given arc can be accessed quickly during route computation.

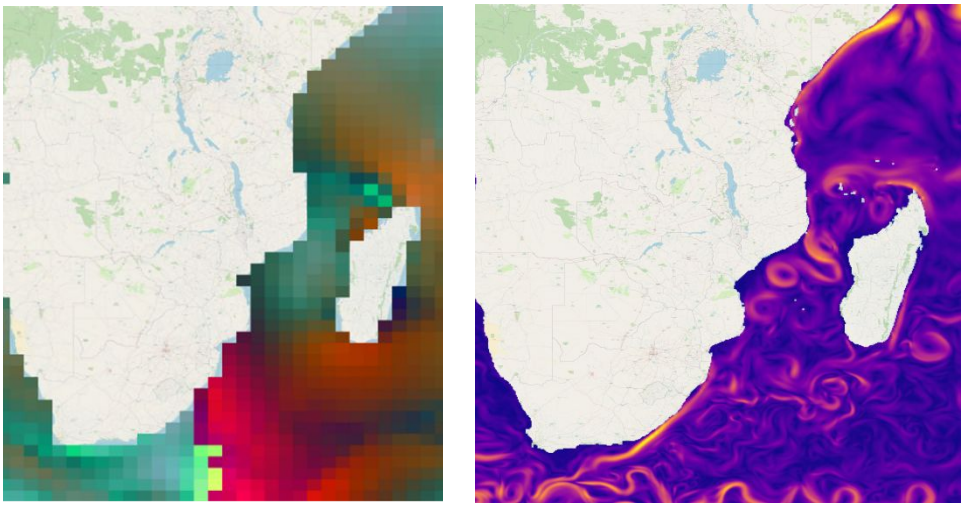

Figure 7. Illustration of raster size of weather data from the east side of South-Africa. On the left, raster size for the wind information; on the right, current information. Data is based on TNM historical weather forecast data (February 2021). Illustration made with QGIS and background map from OpenStreetMap.

Hurricane and Severe Weather Information

Tropical cyclones, including hurricanes and typhoons, are major operational hazards and must be explicitly incorporated into the routing framework. International guidelines specify recommended safe-passing distances based on storm intensity and relative position. Hurricane data are obtained from the Joint Typhoon Warning Center (JTWC) and the National Hurricane Center (NHC), which provide detailed information on the location, projected path, and intensity of each storm (Figure 8). For storms of a minimal Category 1 intensity, datasets also include directional breakdowns of maximum sustained wind speeds.

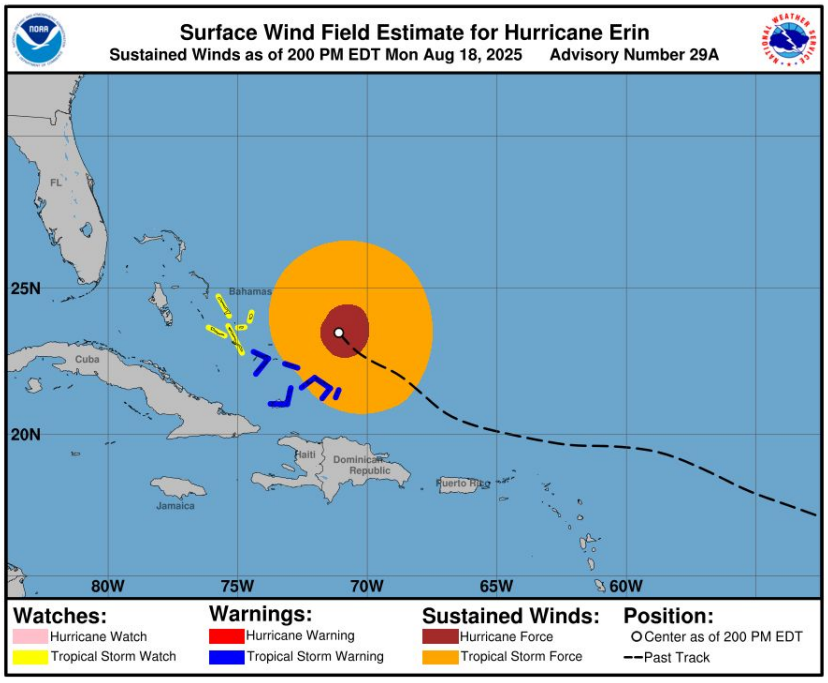

Figure 8. Illustration of information provided for hurricanes and typhoons. Example is based on the hurricane Erin from August 2025. Data and illustration are based on public information from databank at National Hurricane Center and Central Pacific Hurricane Center.

Consistent with industry recommendations, vessels are required to maintain a minimum distance of 200 nautical miles in anticipation of a hurricane or 60 nautical miles after a hurricane. In OptiNav AI, these requirements are enforced directly within the network: arcs violating the prescribed distances are removed entirely. For arcs passing within 200 to 300 nautical miles of a storm, a penalty is added as a soft safety constraint to incentive an additional safety buffer while still permitting the optimization model to evaluate alternative routing scenarios. This integration of hard and soft constraints enables the DSS to navigate severe weather conditions robustly while maintaining operational flexibility.

Static Data

Over the past decade, TNM has routed and monitored more than 20,000 voyages for several thousand vessels, resulting in one of the most comprehensive operational datasets of its kind. Information for each voyage is collected through “noon reports” in which vessel captains provide standardized daily updates to TNM. These reports typically include vessel position, remaining quantities of various fuel types, average speed over the previous 24 hours, local prevailing weather conditions, and other operational details as illustrated in Figure 9.

Figure 9. Illustration of data available in noon reports.

In addition to voyage-level data, TNM maintains detailed technical specifications for each vessel, including hull type, engine characteristics, draft, displacement, and other performance-related attributes. Using proprietary in-house software and algorithms, TNM evaluates vessel performance on an ongoing basis, deriving indicators such as average speed, fuel consumption, weather correction factors, and current-related effects. These continuous assessments support the TNM mandate to ensure that vessels meet their contractual speed and consumption obligations under charter-party agreements.

Collectively, these performance evaluations have contributed to the development of a substantial and highly granular database on the global bulk carrier fleet. TNM has also archived more than ten years of historical weather data, including wind fields, wave heights, ocean currents, and sea-surface temperatures, forming a critical foundation for empirical analysis and model development.

Spatial Network

Each vessel–voyage combination between a given departure and arrival port is modeled on a unique spatial network obtained by discretizing the navigable ocean area into a grid of nodes (or waypoints) connected by feasible sailing arcs. This spatial network must be constructed in a way that captures all feasible routing alternatives and permissible speed settings. The model foundation begins with the spatial node and arc layouts. Because vessels can travel at multiple discrete speeds, each pair of geographically adjacent nodes must be connected by several arcs—one for each possible speed—each with its own travel time and fuel consumption. As a result, the network must represent not only spatial geometry but also the temporal dimension of the voyage.

To capture this temporal structure, each spatial node is associated with multiple discretized time intervals. These time intervals may be set to 60 minutes, 10 minutes, or other resolutions depending on the required precision. Finer temporal discretization increases accuracy and expands network size, sometimes dramatically. Seasonal patterns or long-term weather climatology often imply a preferred routing corridor,

forming the central backbone of the network. A maximum allowable deviation around this corridor defines the spatial width of the network and determines how alternative paths are represented. An illustrative example of a preferred route and associated network layout for a voyage from Buenos Aires to Singapore is provided in Figure 10. More details on the arcs around islands and in the channel is given in Figure 11.

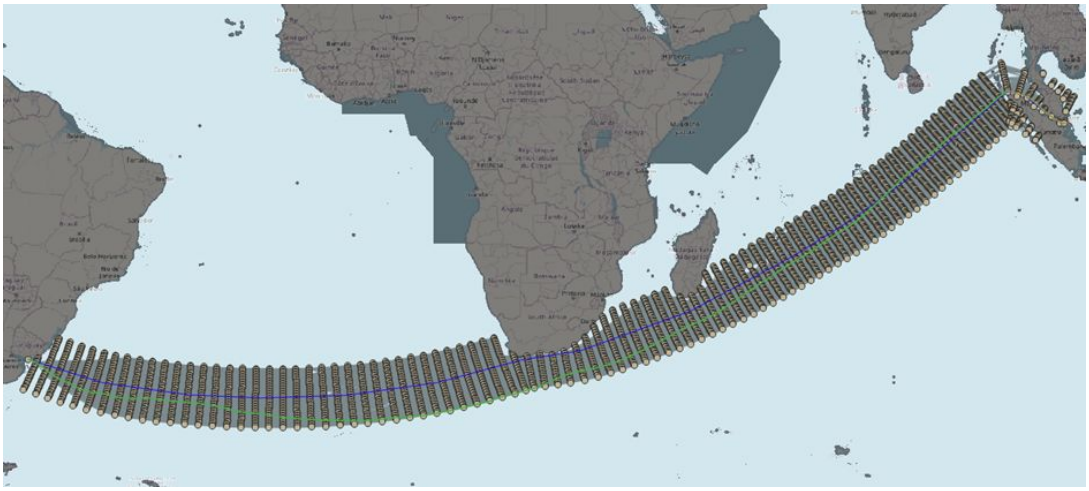

Figure 10. Illustration of preferred path (blue) and optimal path (green) and the spatial network of nodes and arcs between Buenos Aires and Singapore. Illustration made with QGIS and background map from OpenStreetMap.

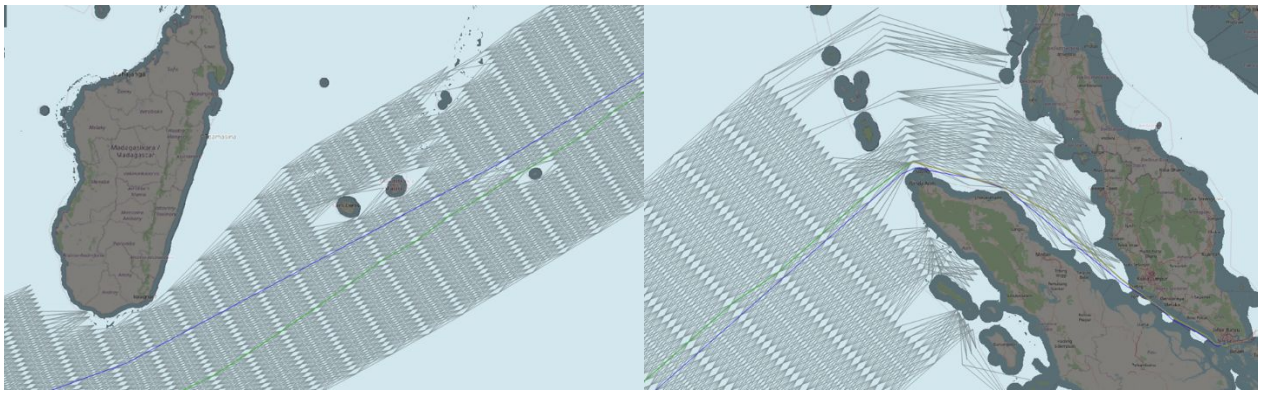

Figure 11. Illustration of spatial network (arcs) around Madagascar and islands (left) and the entrance channel, Strait of Malacca, to Singapore (right) when the feasibility map is used to remove non-feasible arcs. Illustration made with QGIS and background map from OpenStreetMap.

The primary computational challenge lies in evaluating arc-level information—namely, feasibility, sailing time, fuel consumption, safety characteristics, and overall cost. These computations must be performed efficiently because the network can contain millions of arcs and must be processed within seconds in operational settings of DSS usage by planners. The details of these arc computations are discussed in subsequent sections.

Each voyage requires the construction of a dedicated time–space expanded spatial network in which nodes represent spatial and temporal positions, and arcs represent navigational decisions—specifically, choices

of direction and discrete speed or RPM settings. These arcs must face maritime constraints such as established shipping lanes, restricted zones, and geographical obstacles, including islands and shallow waters. Safety considerations are equally critical: arcs must avoid hazardous weather conditions, particularly areas affected by hurricanes, and must account for vessel-specific dynamic stability limitations under adverse sea states.

To determine the optimal route, the system employs a customized Dijkstra's algorithm to identify the minimum-cost path through the network. Multiple variants and implementations of Dijkstra's algorithm exist, each with performance characteristics suited to various network structures. Selecting an appropriate implementation is important to ensure the speed and scalability required for real-time maritime routing.

Because the network incorporates spatial and temporal dimensions, its size can become extremely large, often containing millions of arcs. Consequently, a major challenge lies in generating and evaluating all relevant arc information—feasibility, travel time, fuel consumption, and safety—in a sufficiently short time to be practical for operational route planning. Achieving this requires extensive preprocessing techniques, such as constructing detailed feasibility maps to efficiently identify islands, restricted waters, and other prohibited regions before the network is generated.

Since detailed weather forecasts extend only seven days into the future, additional methods are required to evaluate arcs that fall outside the forecast horizon. Many voyages last up to 30 days; consequently, the system must estimate the likely conditions and resulting delays for the later stages of the route. These approximations must remain computationally efficient while still providing reliable guidance for long-haul voyage planning.

Arc Feasibility

Determining whether a proposed route crosses land or intersects an obstacle is visually straightforward for a human planner, but in a digital environment, this requires a formalized method. To address this, we have constructed a Boolean feasibility map where each pixel indicates whether navigation through that location is permissible. Islands, shallow waters, and other restricted regions are encoded directly into this map, enabling the system to identify infeasible arcs rapidly. During network generation, each arc is checked against the Boolean map, and any arc intersecting a non-navigable pixel is removed. The current feasibility map (Figure 12) uses a spatial resolution of 0.0083 degrees—corresponding to approximately 43,200 longitude points and 20,400 latitude points—providing a highly detailed representation of coastlines and island structures. It requires about 882 million Boolean points.

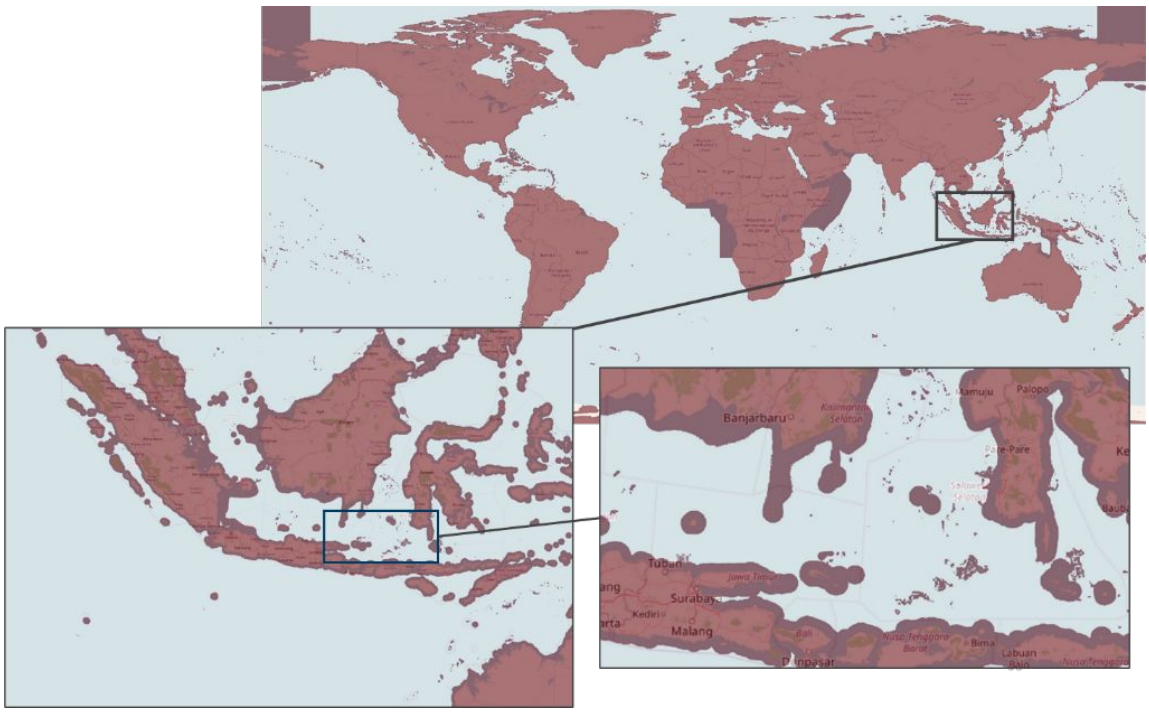

Figure 12. Illustration of the feasibility map and zoomed in parts to identify where an arc is feasible or not. Data based on TNM data and publicly available ocean depth maps. Illustration made with QGIS and background map from OpenStreetMap.

A similar Boolean mapping approach is used for regulatory constraints such as IMO ECAs as described earlier. When an arc traverses such a zone, the DSS automatically adjusts fuel prices or fuel-type requirements. This method is also applied to other no-go zone categories, including regions with documented piracy risk, seasonal or permanent ice coverage, oil and gas platforms, and sensitive military areas.

Some channels and canals impose additional navigational constraints, often requiring pilotage. Examples include the Suez Canal, the Panama Canal, and the Strait of Magellan. The geometry of these waterways is highly intricate, making them impractical to generate dynamically within the main network. For instance, the Strait of Magellan (Figure 13, left) has a length comparable to a single long-distance arc but contains complex curves and narrow passages that cannot be represented using the standard grid-based approach. To manage this, all such channels are pre-generated as separate, high-resolution networks. These channel networks are later merged into the main voyage network, and connection arcs are added where necessary. Pilotage channels also include specific data for transit time (since vessels travel at fixed pilot-controlled speeds) as well as pilotage fees and fuel consumption. The Strait of Magellan presents a particularly important case in routing decisions. Although the alternative southern route in Chile is often used, it is also subject to severe weather due to recurring low-pressure systems that generate strong winds and large waves. As a result, routing through the Strait or remaining offshore is a critical safety and cost trade off decision. In addition, constrained waterways limit routing choices but do not require pilots. These waterways are handled like pilotage channels, with the key difference that vessels retain the ability to vary

speed. Figure 13 (right) provides another example: the approach to Bergen, Norway, where routing is constrained by overhead power lines and bridge height limitations. These examples highlight the importance of incorporating detailed navigational geometry and local restrictions into the network to ensure safe and accurate route planning.

Figure 13. Left: Geometry of the pilotage through the Strait of Magellan in southern Chile. Right: Example of a designated route arriving at Bergen Port in Norway. Illustration made with QGIS and background map from OpenStreetMap.

Performance Functions: Fuel Consumption

Each vessel is associated with a performance curve that characterizes its fuel consumption at various speed settings while accounting for environmental factors such as wind speed and direction, ocean currents, and wave height (Marijan et al., 2025; Handayani et al., 2025). Accurately estimating fuel consumption and vessel speed under varying conditions is challenging because performance depends on numerous vessel-specific characteristics, including length, beam, tonnage, draft, and engine power, as well as the vessel's interaction with surrounding weather conditions. These interdependencies make fuel-consumption estimation a complex modelling task (Psaraftis and Kontovas, 2013; Psaraftis and Lagouvardou, 2023).

Fuel use is a critical economic driver in maritime operations. According to Stopford (2008), fuel costs represent approximately 47% of total expenses incurred during a ship voyage. As a result, incorporating fuel consumption into weather routing objectives is essential for achieving cost-effective and environmentally efficient voyage planning. A recent literature review by Fan et al. (2022) covering two decades of research, categorized ship fuel consumption models into three main types: white box models based on physical and mechanistic principles; black box models, developed through statistical or machine-learning approaches; and grey box models, combining white box and black box elements.

In our research, we developed predictive models for fuel consumption specifically for bulk carriers, leveraging historical voyage data, meteorological conditions, and detailed vessel characteristics. The data underwent extensive cleaning and preprocessing to ensure reliability before modelling. Both machine-learning methods and traditional optimization techniques were applied to generate robust fuel-consumption models capable of reflecting nonlinear interactions between vessel behaviour and environmental conditions. Additional description of the modelling framework and results can be found in Hajli et al. (2024).

Performance Functions–Route Time

Accurately computing vessel speed under varying weather conditions is essential for reliable voyage optimization. Although every vessel is unique, a central concept in modelling performance is vessel resistance, defined as the force required to tow a vessel at constant velocity in calm water. Resistance depends on multiple factors, including vessel dimensions, hull form, displacement, and engine characteristics (Tran, 2023; Deng et al., 2021). When a vessel is commissioned, it undergoes sea trials that establish calm-water performance in ballast and laden. In these trials, the vessel sails along a prescribed path in both directions under favourable weather conditions at various engine RPM settings, enabling an average calm-water speed to be determined. This calm-water performance curve is specific to each vessel and forms the baseline for further analysis.

In practice, however, vessels rarely operate in calm conditions. As vessels encounter wind, waves, and currents, their effective speed at a given RPM diverges from the calm-water benchmark. Estimating this speed reduction is therefore critical. A theoretical framework for assessing speed loss is presented in Kim et al. (2017). In this approach, the total resistance acting on a vessel is computed as the sum of calm-water resistance and additional forces generated by wind and waves (Li et al., 2021; Timas and Mohammadi, 2025). Wind forces depend on wind speed, the attack angle, and the projected wind-exposed area of the vessel. Wave forces depend on wave height, frequency, direction, and hull geometry. By combining these forces, a nonlinear equilibrium problem is solved that identifies the vessel's actual speed at a given power setting. Figure 14 shows a typical result: the green curve indicates the calm-water resistance profile, and the red curve indicates resistance under a specific weather condition. The increased resistance shifts the equilibrium point, resulting in a lower actual speed for the same engine RPM.

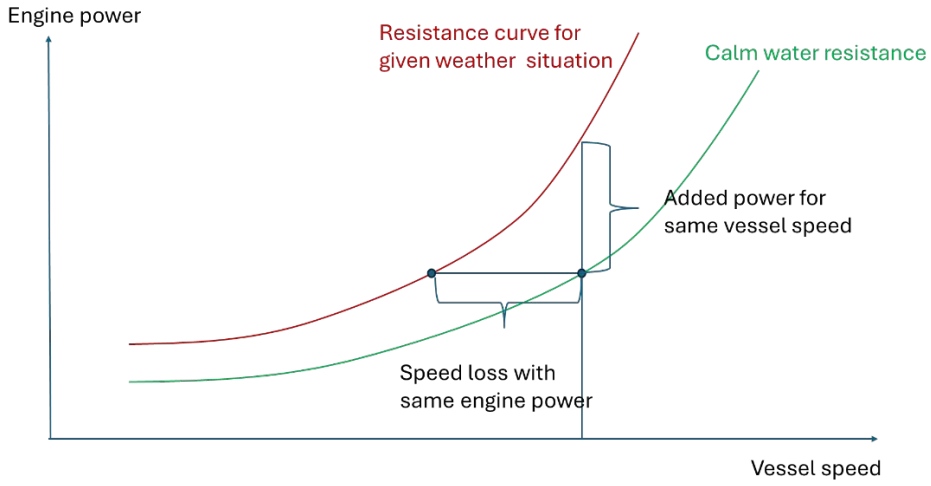

Figure 14. Illustration of the process to estimate speed-loss. The green line corresponds to calm-water forces while the red line is weather-induced forces.

Figure 15 illustrates this phenomenon for two weather scenarios defined by fixed wind speed and wave height. The diagram shows variation in speed loss (or speed gain due to wind assistance) across various relative angles between the vessel's heading and environmental forces. More importantly, the relative

angle must incorporate the ocean current effect that can alter the vessel's effective direction, thus its interaction with the weather. Such diagrams are computed for numerous weather and vessel type combinations to enable a complete performance representation.

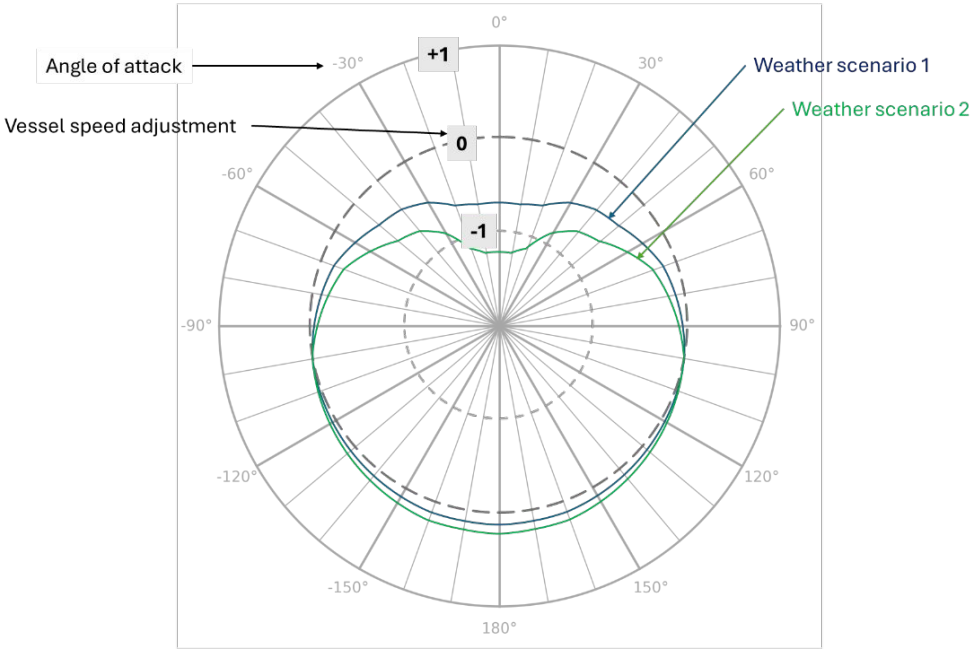

Figure 15. Diagram to show speed loss (knots) (or increase) for various relative angles between the vessel and the two weather scenarios (green and blue curves).

These theoretical results, however, depend heavily on the accuracy of the underlying vessel-specific data, exhibiting inherent limitations. In our approach, we have used the theoretical framework as an initial basis but refined it using observed performance data collected from actual voyages. We have assumed a parametric speed-loss function and solved a least-squares fitting problem in which the theoretical speed-loss profiles are adjusted to match validated observations from the relevant vessel type. The resulting calibrated function, implemented as a spline depending on relative wind direction, wind magnitude, relative wave direction, and wave height, provided a more accurate estimate of speed loss in real operations.

Each physical arc in the routing network can be traversed at multiple calm-water speed settings. When combined with the calibrated speed-loss function, each pairing of arc and speed setting yields a specific travel time. This directly determines the temporal end node of the corresponding arc in the time-expanded spatial network. For example, if five discrete speed settings are available and the arc begins at a given time, the model computes five distinct travel times, each associated with its own arrival time and its own temporal node. This process enables the construction of a detailed and accurate time-expanded network that reflects dynamic interaction between vessel performance and weather.

Safety

Safety considerations play a crucial role in maritime weather routing (Sharif et al., 2024). Figure 16 provides an overview of the various safety criteria using an Ishikawa diagram. Several of these criteria are incorporated directly into the routing framework. For each arc in the network, a quantitative safety measure is computed. The arc is removed (or highly penalized) entirely from the network if it exceeds the allowable threshold for any safety parameter. Arcs with safety values falling within acceptable ranges remain feasible but receive an additional cost penalty proportional to the importance of the corresponding safety aspect. Within the optimization model, safety criteria are implemented in combination with hard and soft constraints (Marjanović et al., 2026).

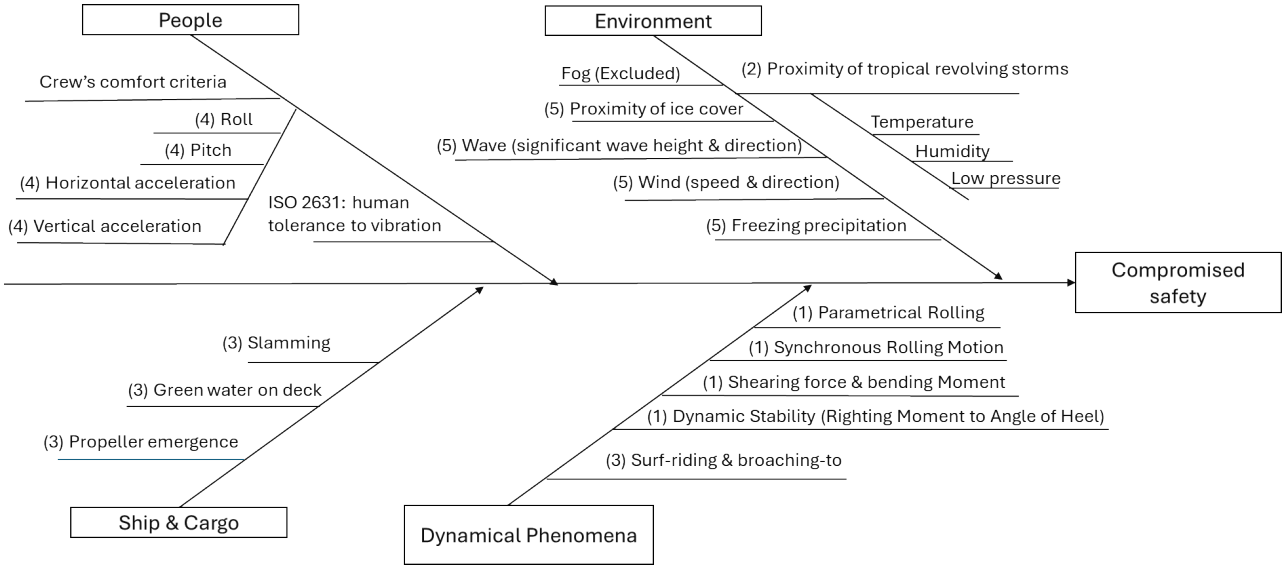

Figure 16. Description of identified safety criteria (and priority 1-5 in brackets) in an Ishikawa diagram. Illustration by Anika Néron.

Of the many possible safety considerations, we are specifically focussing on three key phenomena from the "Dynamic Phenomena" and "Ship & Cargo" branches in Figure 16: dynamic stability (Sharif et al., 2024; DNV GL, 2019), green water on deck, and bow slamming (Sharif et al., 2024; Nielsen, 1987). These hazards significantly influence vessel integrity and crew safety in severe weather conditions. Hard constraints are used to enforce strict feasibility requirements; any arc associated with excessive risk for one of these phenomena is removed. By contrast, soft constraints enable planners to incorporate safety preferences beyond minimum required thresholds by assigning additional cost penalties to arcs representing higher, but still acceptable, risk levels.

To support these evaluations, planners draw on the SHIPX Vessel Responses (VERES; Fathi, 2004) ship-motion analysis system, which provides probabilistic estimates of bow slamming and green water events based on wave conditions, vessel geometry, and motion characteristics. Dynamic stability is assessed by computing the absorbed energy resulting from wind forces and comparing that energy to the vessel's stability limits (Guo et al., 2024; DNV GL, 2019). Together, these assessments ensure the routing model

captures mandatory safety constraints and operator preferences for risk minimization under adverse environmental conditions.

Weather Beyond Forecast Period

Weather forecasts are available only for the first seven days of a voyage, whereas many deep-sea routes may span up to 30 days. Consequently, a significant portion of the voyage must be planned under conditions of weather uncertainty. In manual planning, route planners compensate for this lack of foresight by applying experience-based assumptions about average speed reductions. These assumptions depend on the seasonal period and the geographical region, as dominant wind, wave, and current patterns vary throughout the year. Figure 17 illustrates typical current directions during a particular season; similar climatological patterns exist for prevailing winds and waves. Wave height is especially influential, as it significantly affects vessel delay, and the impact depends on the vessel's travel direction relative to prevailing conditions.

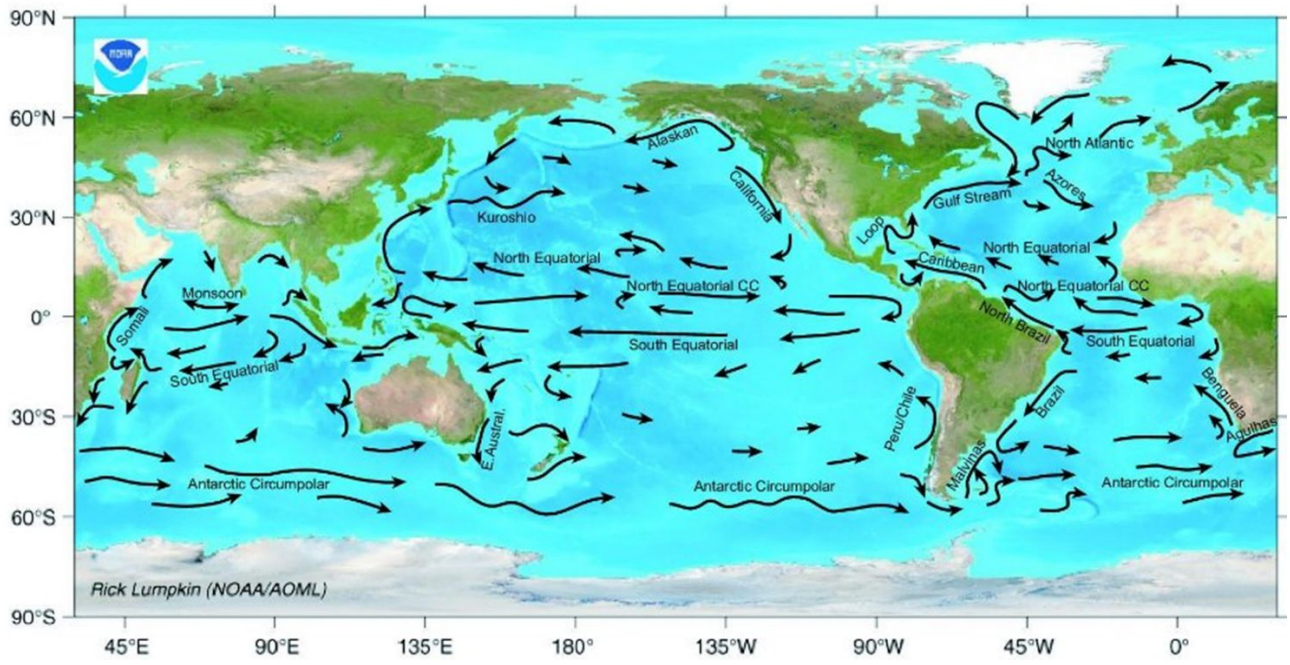

Figure 17. Illustration of the dominating currents and their directions. Illustrations from public databank at National Oceanic and Atmospheric Administration (NOAA).

To replace subjective judgment with a systematic approach, we have constructed *delay maps* that estimate expected speed reductions or delays for any given region and direction of travel. These maps are based on a large archive of historical meteorological data and are generated for each month of the year. Delay maps provide seasonally specific estimates of the expected deviation from calm-water transit time in different directions.

We have employed two complementary methods to construct the delay maps. Both methods begin with a discretization of the global ocean, as shown in Figure 18, using one grid point per degree of longitude and

latitude in all areas where wave data exist, producing a set of 32,596 ocean points with land points removed. The first method computes the average "weather factor" at each grid point using daily historical weather data from the past five years for the relevant month. Described in the Performance Function–Route Time subsection, the weather factor quantifies expected delay using currents (speed and direction), wind (strength and angle), and waves (height and direction). Because the vessel's direction is unknown, delays are computed for eight possible headings at 45-degree intervals. After calculating these directional delay values, a smoothing procedure is applied using radial basis function interpolation. This method assumes that the vessel travels directly through local conditions without route adjustments.

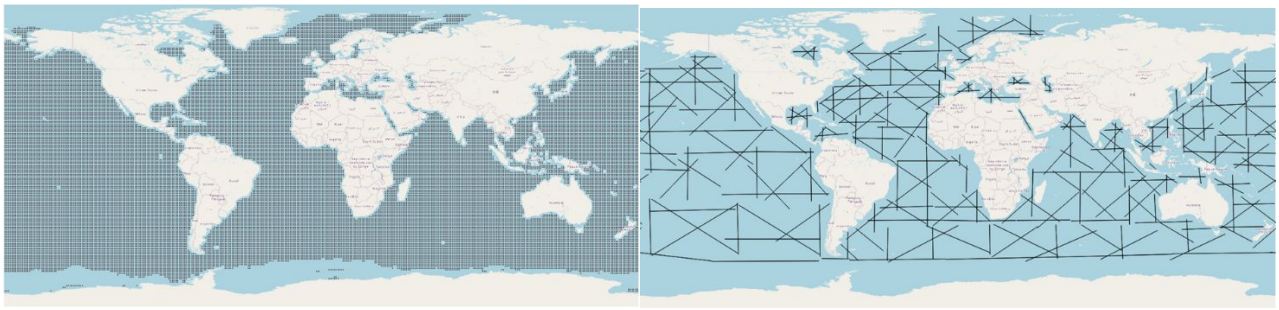

Figure 18. Points used to define the delay maps (left) and arcs used in the second approach (right). Illustration made with QGIS and background map from OpenStreetMap.

The second method incorporates the possibility of local route optimization. In this approach, several longer arcs are defined between selected start and end nodes, each spanning multiple days (Figure 18). For each arc, we compute an optimal route using historical weather for the local period and compare the resulting travel time to the corresponding calm-water transit time. The difference yields an estimated delay for that arc. This value is then distributed to nearby grid points and smoothed using the same interpolation technique. Although more computationally intensive, this method captures the effect of vessels strategically adjusting their path to avoid adverse weather.

An example of the resulting smoothed delay maps is shown in Figure 19 for April 2023, derived from meteorological data for April in the years 2018–2022. The figure illustrates delays for two travel directions—east and west—based solely on wind and wave data; currents are incorporated in a separate delay map. Darker red regions correspond to higher delays; for instance, a value of 1.05 represents a 5% increase in transit time. The westbound delay map exhibits higher delays in Antarctic waters because of strong headwinds and large waves, whereas eastbound delays in the same region are primarily wave driven. In other regions of the world, delays are dominated by persistent headwinds. Although delays can reach as high as 65% in extreme cases, the figure caps value at 20% for visual clarity. All delay maps undergo validation by TNM's experienced planners. For each month of the year, eight distinct directional delay maps are produced.

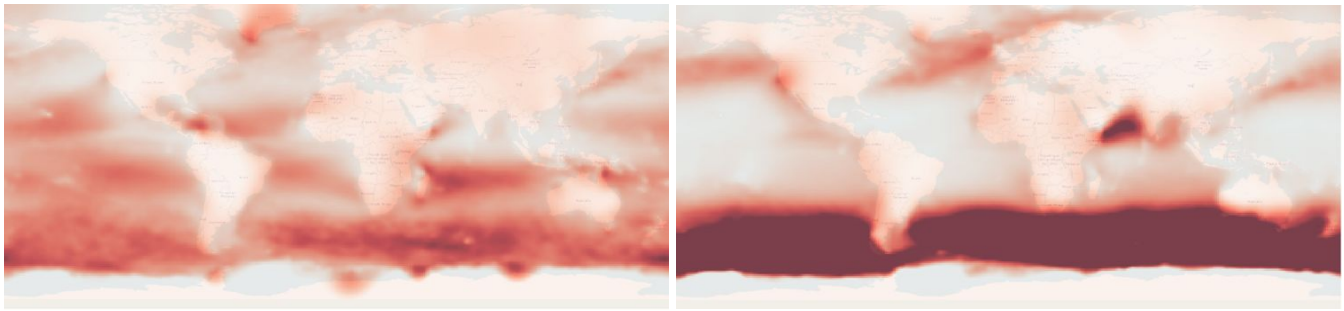

Figure 19. Illustration of a delay map of routes for vessels moving east (left) with a mean value of 1.09 (max 1.19) and west (right) with an average value of 1.05 (max 1.62). Darker areas indicate higher delays. Data from TNM historical weather database. Illustration made with QGIS and background map from OpenStreetMap.

Solution Method

A further challenge in constructing voyage-optimization spatial networks is the sheer size of the time–space representation. For long intercontinental routes, such as from Buenos Aires to Singapore, the potential full time-expanded spatial network becomes prohibitively large, and the time required to generate arc information makes direct computation impractical. Preliminary tests show that building the complete detailed network and computing all arc attributes would require several minutes. This is incompatible with an operational environment where several thousand route optimizations may be performed daily. Consequently, a hierarchical solution strategy is essential for maintaining computational tractability.

The central difficulty lies in the time needed to construct the network and compute the required arc information. Incorporating all details from the outset is computationally infeasible. To overcome this limitation, we have developed a scalable, multi-phase approach that gradually increases the level of detail. A key insight is that detailed networks should be constructed only in regions where the optimal route is likely to pass. By selectively emphasizing computational effort, the system retains accuracy while significantly reducing solution time. The hierarchical solution process consists of three phases:

Phase 1. A preferred route is first identified and a spatial boundary around it is defined; a physical spatial network of nodes and arcs is constructed within this boundary. Each arc includes preliminary information such as feasible directions, possible speed settings, fuel consumption, route time, and safety characteristics, incorporating all feasibility constraints and channel structures. Temporal discretization is not included at this stage. Using the delay maps, a Dijkstra's algorithm is applied to compute the minimum-cost path from every node to the destination node. Each resulting path is stored and represented as an aggregated arc that summarizes the essential characteristics needed for subsequent phases.

Phase 2. Building on the structure from Phase 1, a time-expanded spatial network is constructed with a limited number of speed settings and coarser temporal discretization at the nodes. This portion represents the first seven days of the voyage, for which detailed weather forecasts are available. To account for the

remainder of the voyage, arcs are added from nodes representing all possible positions at the seven-day boundary. The minimum-cost route through this reduced-resolution network is then computed.

Phase 3. The output from Phase 2 provides a preliminary optimal route that integrates forecasted weather and historical delay-map information. In this final phase, the network is restricted to a narrower boundary around this preliminary path, and full-resolution arc computations are performed. This includes the complete set of speed options and a finer temporal discretization. As in Phase 2, arcs extending beyond the seven-day forecast horizon are included. Solving the optimization problem at this level of detail yields a refined route with accurate estimates of sailing time, speed profiles, and fuel consumption.

Multi-Objective Optimization

The route optimization problem is formulated as a multi-objective decision model incorporating several cost components. Primary contributors are fuel consumption and chartering cost; the latter is directly related to voyage duration. Additional components reflect safety considerations such as avoiding hurricanes or regions where dynamic stability may be compromised (Figure 20). In our framework, these factors are combined using a weighted objective function, where the selection of appropriate weights is essential to capturing vessel owner and charterer preferences. Though assigning weights for fuel consumption and voyage time is relatively straightforward (since both can be expressed in monetary terms), the integration of safety-related criteria introduces additional complexity, as their valuation is less direct.

Figure 20. Illustration of the complex process to balance multiple objectives (for example, safety, cost, and time). Illustration by Maxime Houssin.

To address this challenge, we have developed a methodology based on machine learning principles and inverse optimization (Sharif et al., 2025). The core idea relies on access to a set of "best practice" routes—historical voyages that experienced captains and planners regard as optimal under the prevailing conditions. Because these routes can be quantified in detail, they can be treated as optimal solutions of a weighted multi-objective routing problem. The next task is to infer the set of objective weights that make these best-practice routes optimal. This is a classic inverse optimization problem (; Rönnqvist et al., 2017).

Results and Benefits

DSS OptiNav AI

A major challenge in the implementation lies in designing the algorithms and systems required to process all available data and compute optimal settings with a reasonable computational time. There is also a need to develop learning processes and models to recursively revise performance curves as more data is collected. The project requires a multidisciplinary team covering areas such as optimization, analytics, AI, Big data, computer science, GIS, business models, and business intelligence. With decision support tools, TNM can assist vessel companies in navigating the new complexities of operating in a cost-effective manner. This enables vessel operators to make better business decisions that in turn will allow for cost savings while also reducing company's carbon footprint. OptiNav AI was put in production during fall 2022. With this DSS, the planner had access to a set of various objective priorities (time, fuel, emissions, safety, or fixed arrival times) and constraint settings and performed multiple route analysis quickly. The system was also available for TNM customers to analyze best vessel configurations for transport assignments. Since then, the OptiNav AI decision support system has been continuously revised. The overall user interface was developed by Papersoft Technologies. OptiNav AI is meant to be a key tool in a complete decision theatre where TNM has a close connection with its clients, ship owners and captains, as illustrated in Figure 21. In the long term, all stakeholders will implement OptiNav AI at the local level.

Figure 21. Illustration of a decision theatre where TNM, clients, and captains work together to manage the overall routing of a vessel. Illustration by Maxime Houssin.

OptiNav AI consists of a set of software modules implemented on a large server, allowing multiple users to run simultaneously. The main modules are the user interface; data management for (i) the weather information; (ii) vessels and performance functions; (iii) feasibility map, delay maps and channels; and the optimization module. In addition, modules manage and compute delay maps based on historical data, weather factors, and some performance functions. Data for new vessels are collected continuously. When a new vessel is contracted for TNM services, the captain receives a form with detailed questions to collect

key information about the vessel's performance. Typical information collected includes vessel type, engine type and fuel type, speed and fuel consumption, and various levels of load and RPM settings. Detailed weather information is received from Frivind in Norway multiple times during the day. Weather data is then stored in an efficient format for fast input to the optimization within OptiNav AI. The data needed for a full seven-day forecast takes 216 MB of compressed data in GRIB format (standardized weather data format). Information about hurricanes is downloaded from the joint hurricane and typhoon centre.

Planning a route follows a process. First, the planner chooses the ship to draw the plan. If no detailed ship exists in the database, a sister ship with similar characteristics is chosen. Additional information regarding ship type or other ship information can be selected or revised. Second, the start port and estimated departure time (ETD) are selected, followed by the end port and any preferred ETA selection. Third, the preferred route for the given season is displayed in the map system. Fourth, the planner selects fuel types and costs that the engines are using. Fifth, the planner decides if the vessel follows a so-called preferred route (with specified speed setting) or if optimization to identify the best speeds is used. A key selection is the use of a set of predefined objective functions, for example, lowest cost, lowest time, lowest emission, specific ETA, or a hybrid version. Lastly, optimization is performed and results are shown in the map and result reports. The map includes waypoints as well as related speed setting and actual speed together with information about route time and fuel consumption.

Figure 22 shows the screenshot from the preferred route (blue) and optimized route (green) between Buenos Aires and Singapore. Figure 23 provides summary results from the route. These include route time, fuel consumption, and the diagram of estimated speed on ground (green) and wind speed (red).

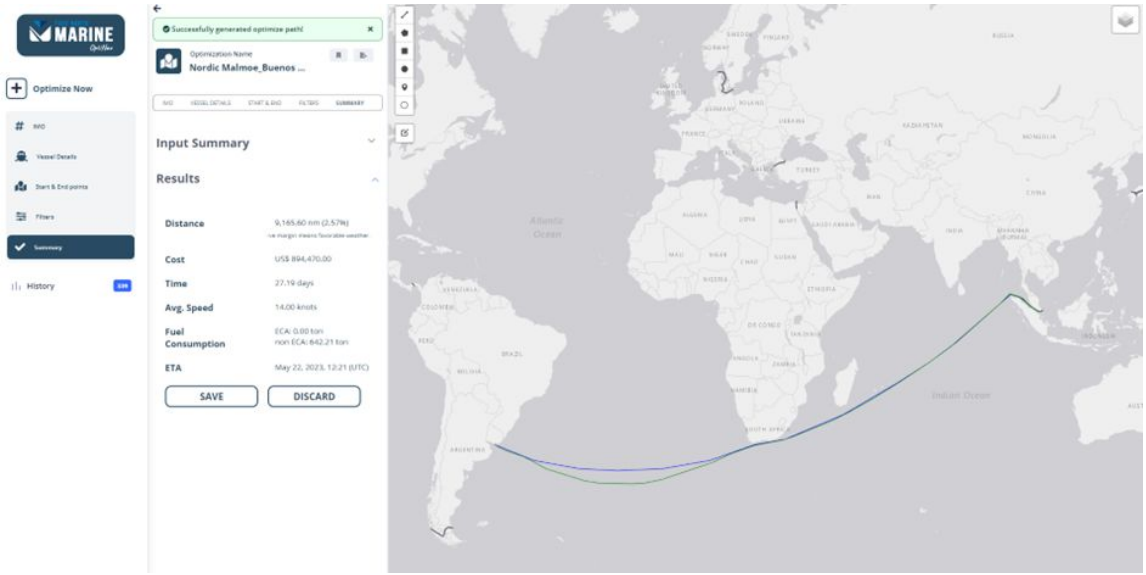

Figure 22. Screenshot from DSS OptiNav AI of preferred route and optimized route between Buenos Aires and Singapore on April 24, 2023.

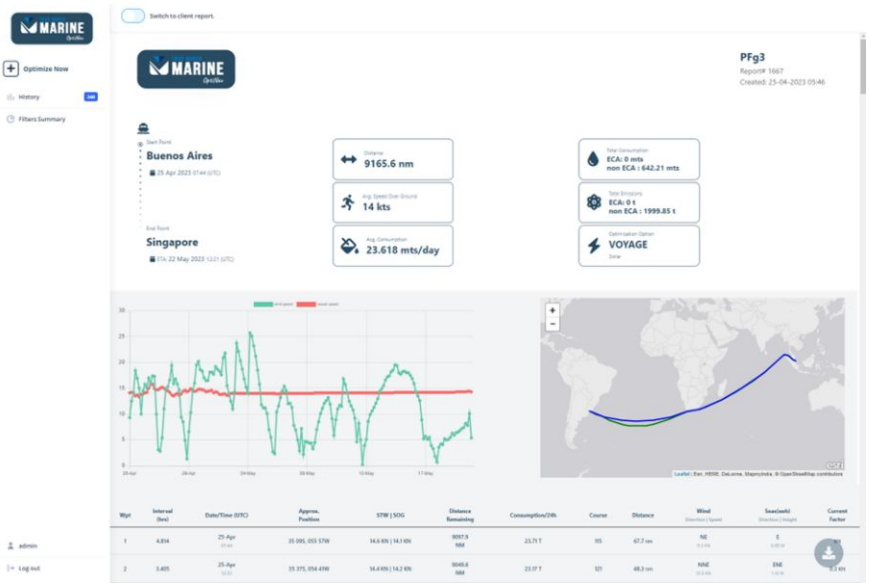

Figure 23. Screenshot from OptiNav AI of summary information about the optimized route between Buenos Aires and Singapore on April 24, 2023.

Users and Industry Dynamics

The maritime industry is characterized by longstanding structural tensions between shipowners and charterers, largely stemming from differences in incentives and the contractual framework governing voyage performance. Owners often portray vessel capabilities in the most favourable light, whereas charterers may assert underperformance to obtain financial adjustments after a voyage. These opposing interests have generated chronic mistrust and limited the availability of accurate performance data. Compounding this issue is the practice of updating vessel positions only once per day, resulting in aggregated and often unreliable data that reduce the quality of performance estimations. Resistance to technological change, especially among ship captains and operators accustomed to traditional navigational approaches, further complicates the adoption of data-driven systems.

Despite these challenges, the potential economic and environmental benefits of optimization have begun to shift industry attitudes. Stakeholders increasingly recognize that more accurate data and collaborative information exchange can lead to significant operational improvements. Within TNM, planners represent a key user group for OptiNav AI as they possess varying experience levels and undergo approximately three weeks of structured training, during which they work through real cases and daily exercises. As a result, planners have now integrated OptiNav AI into their routine workflows and continuously provide feedback that guides future enhancements.

The TNM client base includes several large partners that collectively represent a substantial share of the company's activities. These clients contribute actively to the refinement of the user interface and the adjustment of system functionalities. In comparison with competing systems, a central differentiator of OptiNav AI is its human-in-the-loop approach. Though many competitors rely exclusively on SaaS models that automate routing recommendations, TNM places analysts at the centre of an open decision-

theatre environment where human expertise complements algorithmic outputs. This integration ensures that optimization results comply with operational constraints, qualitative rules derived from experience, and the inherently unpredictable nature of maritime navigation.

Impacts

From a computational standpoint, OptiNav AI demonstrates strong performance even on large and complex routing problems. For representative long-distance voyages, OptiNav AI can generate and solve extensive networks consisting of hundreds of thousands of arcs and tens of thousands of nodes within seconds. Total solution time averages a few seconds, including data loading, network generation, and computation, thereby enabling near real-time decision support.

Operationally, OptiNav AI has substantially impacted how voyages are planned and executed. Clients can now specify objectives such as earliest arrival time, lowest-cost routing, or minimal emissions, and OptiNav AI determines optimal speeds and routes based on vessel characteristics and weather forecasts. Across a large sample of operations, OptiNav AI has delivered average fuel savings of approximately 3.5%, corresponding to about one to one-and-a-half metric tons of fuel saved per day for a typical bulk carrier. In practical terms, this equates to roughly 1,500 litres of fuel per day, or the equivalent fuel capacity of about 30 passenger cars. When such savings are projected across fleets of several hundred vessels, the environmental and financial impacts become significant. With 700 vessels, this exceeds USD 180 million annually with a fuel cost of USD 500 per metric ton.

Although the quality of decision making has improved, the introduction of OptiNav AI initially resulted in longer planning times for analysts. Longer planning times were primarily due to the need to assemble more detailed vessel performance profiles and review daily optimization outputs through human oversight. Planned improvements to user interface design and automation are expected to reduce these times substantially. Another important impact relates to regulatory compliance: OptiNav AI provides reliable support for monitoring and reporting GHG emissions and ECAs respect, thereby helping operators comply with evolving environmental standards.

It is also possible to perform simulations on a large set of voyages with detailed weather information including all weather forecasts. In these simulations, it is possible to evaluate the balance of costs and safety based on the typical weather variations throughout the year. Other important insights are the benefits of delay maps and the replanning frequency.

Implementation Challenges

Several challenges impacted the implementation and adoption of OptiNav AI. High-quality data acquisition remained a significant barrier. Fuel oil consumption records, engine-power correlations, and other critical performance inputs were often difficult to obtain due to privacy concerns, proprietary data policies, and inconsistent onboard measurement systems. Accurate models require access to telemetry, onboard sensors, and fleet management databases, as well as adjustments for external influences such as

weather, load, and maintenance conditions. Because these conditions are rarely uniform, data quality varies considerably, affecting the robustness of optimization outputs.

Usability remains an ongoing concern. Although many planners appreciate the efficiency gains from optimization, others find interfaces challenging or insufficiently flexible for manual adjustments. Change management presents additional obstacles, as many captains and operational staff remain skeptical of algorithmic decision-making. Effective training programs and transparent communication of benefits are essential to address these concerns. Another challenge involves establishing confidence in the system's recommendations. Stakeholders require evidence that optimization results are reliable and the system yields tangible operational and financial benefits. Demonstrating return on investment—including direct savings and long-term improvements—is critical to fostering broader adoption. Lastly, as long as data remain inconsistent or incomplete, optimization accuracy will depend heavily on planners' ability to evaluate and adjust algorithmic outputs.

Future Work

The maritime sector faces increasingly stringent decarbonization targets, particularly for 2030 and 2050, which will continue to drive the development of more advanced, robust, and adaptive optimization systems. Future DSS platforms will need to incorporate sophisticated AI-based predictive models capable of quickly responding to unanticipated disruptions such as geopolitical instability, shifting trade regulations, extreme weather, or sudden changes in environmental compliance requirements. These adaptive algorithms will play a central role in ensuring routing decisions remain operationally feasible and environmentally compliant.

Another important direction for future development concerns system interoperability. As vessels increasingly integrate IoT-based monitoring systems and ports adopt automated digital infrastructures, DSS platforms must be able to interface seamlessly with a broad range of technologies and legacy systems. Achieving such interoperability will require new standards for data exchange as well as coordinated efforts among shipowners, operators, ports, and technology providers. The ability to handle vessel-specific performance variability will also continue to improve. For example, LNG carriers exhibit sloshing effects that require specialized computational treatment, and other vessel classes likewise possess unique behavioural characteristics in addition to emerging eco-innovations such as wind-assisted propulsion. Enhanced machine-learning models for predicting arrival times and optimizing voyages will enable more accurate, vessel-tailored routing.

Finally, significant improvements in user-centred design are expected. More intuitive interfaces, rapid scenario-comparison capabilities, and automated data ingestion will reduce the current workload associated with planning and monitoring. As these enhancements materialize, the industry will likely shift toward more widespread adoption of optimization tools, provided that solutions can demonstrate clear economic value and operational benefits while accommodating the complex, heterogeneous nature of global shipping.

Conclusions

This work has presented the design, development, and implementation of an advanced DSS that serves as a central tool for modern maritime weather routing. The system integrates multiple layers of analytics, combining quantitative information derived from weather forecasts, vessel characteristics, and operational constraints with qualitative knowledge contributed by experienced planners and ship captains. This fusion of data-driven modelling and experiential expertise has proven essential in addressing the growing complexity of maritime operations, particularly as new environmental regulations introduce GHG emissions as a critical third cost dimension alongside fuel consumption and hire rates.

A central contribution of this research is the construction of a detailed optimization network that captures the full set of navigational, meteorological, and vessel-specific factors relevant to voyage planning. Despite the scale and complexity of these networks, often involving hundreds of thousands of arcs and tens of thousands of nodes, the specialized solution approach enables near real-time computation. This capability enables planners to quickly evaluate multiple routing scenarios and adjust decisions dynamically as weather conditions and operational requirements evolve.

The operational deployment of OptiNav AI has demonstrated its substantial value. Empirical results show that the system consistently reduces fuel consumption by approximately 3.5% on average, translating into significant annual savings in operating costs and GHG emissions when scaled across large fleets. Users have also reported improvements in decision quality, regulatory compliance, and situational awareness, even as the introduction of richer data requirements has initially increased planning time. The human-in-the-loop design has been particularly effective in building trust among industry stakeholders, ensuring that optimization outputs remain transparent, explainable, and closely aligned with real-world constraints.

The system has already gained traction among major clients who have contributed to iterative improvements in functionality and user interface design. Published research underpinning OptiNav AI, together with strong operational results observed to date, provides convincing evidence of its capabilities. These achievements position TNM to expand its client base globally and play a leading role in the digital transformation of maritime voyage planning and to contribute to the shipping sector decarbonization.

As the industry moves toward stricter environmental targets and greater reliance on data-driven decision making, tools such as OptiNav AI will become increasingly indispensable. Continued development, particularly in the areas of adaptive algorithms, automated data integration, port-vessel logistics coordination, and enhanced modelling of vessel-specific behaviours, will further strengthen the system's ability to support sustainable, efficient, and resilient maritime operations.

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