

THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Voyage optimization algorithms for ship safety and energy-efficiency
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CHALMERS UNIVERSITY OF TECHNOLOGY
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Abstract

Currently, over 90% of the world's trade is transported by sea. The environmental impacts from shipping and societal challenges of human and property losses caused by ship accidents are pressuring the shipping industry for more energy efficiency and enhanced safety. In the maritime community, voyage optimization systems are recognized as one of the most effective measures that can contribute to the sustainability of the maritime sector. A voyage optimization system can provide an optimized ship route for an expected time of arrival (ETA) with well-planned waypoints and sailing speeds for a specific voyage, minimizing fuel consumption and structural damage due to vibrations. The optimization procedure accounts for reliable meteorological and oceanographic (MetOcean) forecasts and exploits accurate ship's performance models, which can describe the ship's speed-power relationship, motion and structural response, etc. in terms of various MetOcean and operational conditions.

Various optimization algorithms are available to provide route planning services in the shipping market. However, these algorithms often contain large uncertainties, leading to a large scatter of the recommended optimal route solutions. Furthermore, these algorithms focus on simple voyage optimization problems, e.g., maintaining a fixed ship speed during the entire voyage, and their results may be impractical for actual ship operation. Moreover, most of the algorithms focus on single-objective optimization. Therefore, the main goals of this thesis are to 1) study the uncertainties and sensitivities of various conventional routing optimization algorithms, 2) analyse the benefits of these algorithms for ship safety and fuel consumption, and 3) propose a more sophisticated voyage optimization algorithm to provide a globally optimal ship route plan to guide actual ship operation.

In this study, five conventional voyage optimization algorithms, categorized as either dynamic grid based methods or static grid based methods, are benchmarked to identify their advantages and disadvantages and their relationships. The benefits of using various optimization algorithms to reduce crack propagation in ship structures are investigated. It is concluded that crack propagation can be reduced more than 60% by applying a voyage optimization algorithm. Finally, a hybrid of Dijkstra's algorithm and a genetic optimization algorithm is proposed to search for globally optimum solutions for routes in a 3D graph. It was found that the hybrid algorithm can solve multi-objective route optimizations, helping ships avoid multiple severe sea conditions. The algorithm can additionally provide optimum route suggestions, allowing for both voluntary ship speed and power variation along a route. It is concluded that the algorithm can design optimum ship routes with the lowest fuel costs while ensuring an accurate expected time of arrival.

Keyword: Energy efficiency; Expected time of arrival; Dijkstra's algorithm; Genetic algorithm; Ship safety; Voyage optimization algorithms

Preface

This thesis is composed of the research work performed at the Division of Marine Technology, Department of Mechanics and Maritime Science at Chalmers University of Technology, during June 2016 to June 2018. The work is funded by EU FP7 Space-based Maritime Navigation (SpaceNav) and EU Horizon2020 Earth Observation for Maritime Navigation (EONav) projects.

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Gothenburg, June 2018

Helong Wang

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List of appended papers

For all the appended papers, the author of this thesis contributed to the ideas presented, planned the paper with co-author, did most of the programing and wrote the majority of the manuscript.

- Paper I** Wang, H., Mao, W., and Eriksson, L. E. (2017). Benchmark study of five optimization algorithms for weather routing, Proceedings of the ASME 2017 36th International Conference on Ocean, Offshore and Arctic Engineering (OMAE2017) in Trondheim, Norway, June 25-30, 2017. OMAE2017-61022.
- Paper II** Wang, H., Mao, W., and Zhang, D. (2017). Voyage optimization for mitigating ship structural failure due to crack propagation. Journal of Risk and Reliability, pp.1-13. DOI: 10.1177/1748006X18754976
- Paper III** Wang, H., Mao, W., and Eriksson, L. E. (2018). MetOcean data driven voyage optimization using genetic algorithm, Proceeding of the 28th International Society of Offshore and Polar Engineers (ISOPE 2018), Sapporo, Japan. ISOPE2018-TPC-0446.

List of other published papers by the author

- Paper IV** Eriksson, L., Ye, Y., Jonasson, L., Qazi, W., Mao, W., Wang, H., Möller, J., Lemmens, K., and Dokken, S. (2018). EONav – Copernicus data in support of maritime route optimization, Proceeding of the 2018 International Geoscience and Remote Sensing Symposium (IGARSS 2018) in Valencia, Spain, July 22-27, 2018.

1 Introduction

Reducing environmental impacts and promoting economic benefits from shipping are two of the most important current issues in the maritime community. Although shipping is the most energy-efficient form of freight transportation, it still represents a substantial source of greenhouse gas emissions (up to 3% of global emissions), emitting approximately 1 billion tons of CO₂ every year (Smith et al., 2015). Furthermore, fuel costs represent approximately 50-60% of a ship's total operating costs. Using a large modern vessel as an example, with the cost of bunker fuel at 550 USD per ton and fuel consumption of 220 tons per day, a one-month round trip voyage for this vessel would cost approximately 3 million USD. The direct cost impact is the key incentive for energy efficiency of the shipping companies in acknowledging their environmental footprint. According to the shipping market survey conducted by DNV-GL (2015), shipping companies have become more willing to invest in simple and cost-effective technologies to reduce fuel cost and air emissions from their ships. And among all available energy-efficiency solutions, the most recognized measure is a voyage optimization system, which more than 80% of the respondent shipping companies had planned to be implemented or already installed in their ships.

Additionally, ship safety has always been of interest in the shipping industry. According to AGCS (2017), the total number of ship losses rose to 85 during 2016. Among all the causes of vessel loss, sunk/submerged is the most common, up to 46 losses. Over half of the sunk/submerged losses were driven by bad weather. Bad weather causes not only vessel loss but also structural damage and cargo losses, or even loss of human crew life. Advances in weather monitoring and forecasting are widely used in ship navigation to avoid severe weather and enhance ship safety at sea. For modern ship operations based on weather forecasts, a voyage optimization system can not only help to avoid bad weather but also to find routes that can minimize transit time and fuel consumption without placing the vessel at risk of weather damage.

1.1 Background

In the early stages, the main purpose of a voyage optimization service/system was to provide primary guidance to ships to reach a ship's destination as quickly as possible, based on forecasted weather conditions and possibly also on a ship's characteristics and operational capabilities (Bowditch, 2002). As the price of oil and social awareness of air emissions from the shipping industry have increased rapidly, voyage optimization systems now can currently provide optimum routes for ocean voyages.

Several weather-routing systems are available in today's shipping market to provide voyage optimization services; Storm Geo, WNI, GAC SMHI Weather Solutions, etc., are among the top of the list. Storm Geo (2018) provides a recommendation for the optimal route taking into account analysis of all variables, including the weather, currents, the type, speed, age, and stability of the vessel, and its cargo. It has developed a voyage optimization system using artificial intelligence with an extensive alarm system that continuously monitors the vessels and alerts the Route Analyst when action is needed. The alerts are prioritized so the analyst can quickly address those vessels that need help most urgently. These alarms cover all facets of the voyage including administrative details, data quality, ship energy performance, severe motion, etc. WNI (2018) offers a weather-routing service and provides safe and economical options for routes and engine RPM to achieve profits for operators with ship-specific performance models. It gives options for voyage

optimization such as least cost (time cost and fuel cost), required time of arrival (RTA) with least fuel, speed-based routing, etc. It offers a multiple engine setting service for routing optimization. GAC-SMHI Weather Solutions (2018) offers a package that includes on-board weather routing and online performance analysis, which provides the basic information for making proper decisions for ship routing. It is less skilled in good automatic calculation, and the final detailed calculation is expected to be done by the master using an on-board routing tool.

An overview of a typical voyage optimization is shown in Fig. 1. A voyage optimization system consists mainly of the weather data model, the ship performance model, the constraints for sailing, and the voyage optimization algorithms. The input data includes weather forecast information, a ship's performance models and sailing constraints. The weather data model provides weather forecast information about encountering Meteorological and Oceanographic (MetOcean) conditions. The ship performance models are used to estimate a ship's operational performance at sea. They are also related to the objective values (such as fuel consumption during the voyage) that should be optimized. The constraints contain the information of traffic lanes, shallow water, etc. The voyage optimization algorithms provide optimal routes for different objectives based on forecasts of weather, sea conditions, the constraints and a ship's individual characteristics for a particular voyage. An optimum route refers to the optimization results for different objectives such as minimum fuel consumption or minimum voyage time.

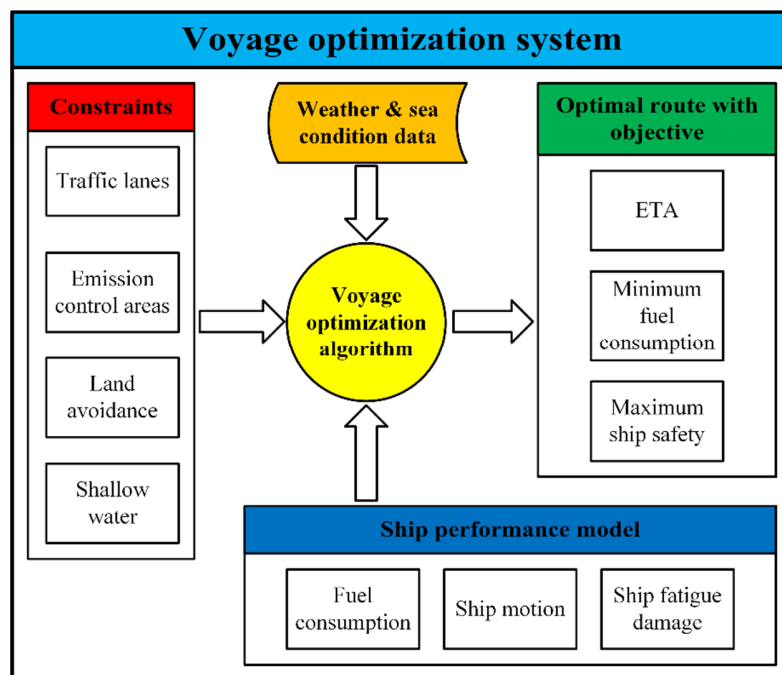


Fig. 1. Overview of voyage optimization system

In both the research and industry domains, there are numerous on-going projects to develop better weather routing systems for the shipping end-users. Different projects have their focuses invested in one or several of the components in Fig. 1. For example, the top three weather routing providers listed above have been continuously developing and upgrading their systems with respect to more reliable MetOcean weather forecasts, user-friendly interfaces, etc. Development in academia focuses more on developing and integrating robust and reliable ship performance models, e.g., Mao

et al., (2016), Tillig (2017). The optimization algorithms are often either directly implemented from existing methods or adopted from other engineering fields. In the following, the state-of-the-art development status of voyage optimization algorithms is presented first, followed by the motivation and objective of this thesis study.

1.2 Literature review of voyage optimization algorithms

In a voyage optimization system, the multiple objectives of minimum fuel consumption and expected time of arrival require a speed-power performance model of the ship in various operational conditions (Notteboom et al., 2009). Another basis for the multi-objective optimization is the mathematical optimization algorithm, which can help to plan a route associated with certain ship speeds to avoid adverse weather and sea conditions. Thus, the optimization algorithm is the most crucial part of a voyage optimization system.

From a methodological perspective, voyage optimization algorithms can be divided into two categories for route planning: specific optimization algorithms, and general optimization algorithms. Here, specific optimization algorithms mean that the algorithms are designed mostly for routing optimization such as the Modified Isochrone method (Hagiwara, 1989) and the Isopone method (Klompstra, 1992). General optimization algorithms such as Dijkstra's algorithm (Dijkstra, 1959) are used to solve general optimization problems in which users define their own models for specific problems such as path-finding problems in games. In the following, the review begins with a discussion of specific optimization algorithms for route planning.

1.2.1 Specific optimization algorithms for route planning

The Isochrone method was first introduced by James (1957). An Isochrone is defined as a geometrical time front, which is a boundary that is achievable for a ship during a certain time interval. Hagiwara (1989) modified the method to be more suitable for computerization. The method can generate a ship route with minimum time cost. It can also be used to obtain a ship route with a minimum fuel cost by recursively adjusting propeller revolutions (or engine power) for a minimum time-of-arrival route. By varying the propeller revolution speed or engine power input, a ship's speed will also be changed accordingly. The method is also able to estimate the standard deviations of elapsed time and fuel consumption with the stochastic minimum time/fuel routing. The problem is that the adjustment for propeller revolution speed is based on a constant ship speed during the whole voyage instead of adjusting it at various sailing stages. The assumption of a fixed ship sailing speed, e.g., as the service speed, may help the ship to find globally optimum route solutions. However, in reality, an ocean-crossing ship never sails at constant speed, particularly during storm conditions. If speed variations are allowed during the optimization process, these algorithms will not be able to provide a globally optimum ship route for a specific voyage. (Simonsen et al., 2015; Wang et al., 2017).

Klompstra (1992) introduced the Isopone method, which is similar to dynamic programming in that it is a recursive algorithm. It is based on the modified Isochrone method; it is an extension of the Isochrone method, and extends its search region into a three-dimensional sailing space by adding the time dimension into the geographic sailing regions. Its difference from the modified Isochrone method is that it creates energy fronts instead of time fronts. A fixed fuel unit is regarded

as a grid resolution parameter in the Isopone method and is similar to fixed time units. Since it uses a deterministic relationship function between speed and fuel, it can also be regarded as a two-dimensional search method. The fixed fuel unit being treated as somehow an interval relies heavily on the accuracy of the ship fuel-speed model. Given that the ship fuel-speed model is a reverse model that is not well developed, this method is not much used in practice.

Lin et al. (2013) proposed a three-dimensional modified isochrone method for determining optimized ship routes. It utilizes the recursive-forward technique and a floating grid system. The recursive-forward algorithm for optimizing ship routing employs the weight (voyage progress) as a state variable. The advantage of the three-dimensional modified isochrone method is that it allows the ship speed and wave heading angle to vary with geographic locations. In addition, it is used not only for minimizing the ship route as well as ship resistance but also in advance for enhancing safety during the voyage.

1.2.2 General optimization algorithms for route planning

The algorithms that have been developed as general optimization tools and adopted for ship voyage optimization are categorized into, e.g., dynamic programming, genetic algorithms, and path-finding methods.

Dynamic programming

Based on predefined two-dimensional waypoint/grid systems, Chen (1978), Calvert (1990) and De Wit (1990) employed a search method for voyage progress as the stage variable and used a backward algorithm implemented with dynamic programming. The advantages of dynamic programming are two-fold. First, in a time-optimal route, once a waypoint is evaluated for the best time of arrival, the later waypoints in the grid system can also be evaluated without making a new dynamic-programming search. Second, this type of method allows for considering navigational constraints. In De Wit (1990), route planning using constant propeller revolution speed is proposed for both computationally and practically efficient optimization, since allowing for varying propeller revolution speeds in the optimization process could lead to serious computational difficulties at that time. Furthermore, a new grid system was also proposed to replace the time front as in the Isochrone method.

The 3D dynamic programming introduced by Shao et al. (2012) is based on original dynamic programming proposed by De Wit (1990). It is constructed to optimize both a ship's sailing speed and its heading in the route planning. If speed variation is allowed during the optimization process, the computational effort required by this method increases exponentially. It uses a float state technique to reduce iterations in the process of optimization to save computational effort and uses a discretized range of speeds in iterations to calculate the best speed-variation profile for the pre-defined objective function. During each iteration, one optimal state is chosen as the parent for the next state.

Zaccone (2018) demonstrated another 3D dynamic-programming-based ship voyage optimization method that attempts to select the optimal path and speed profile for a ship voyage based on weather forecasts. Three variables are concerned: start and arrival points and time instants. The search domain is progressively explored following a breadth-first approach. Nodes are sorted by priority

to minimize the estimated number of segments. A number of nodes characterized by a time of arrival and a cost are identified at the end of calculation. The solutions given by each end node form a Pareto-Frontier of a two-objective optimization problem.

Genetic algorithm

Hinnenthal (2008) proposed a multi-objective genetic algorithm that stochastically solves a discretized nonlinear optimization problem. For an efficient optimization, a ship's sailing course and velocity profiles are represented by parametric curves. The objective to be optimized in this paper is two sets of parameters that control the parametric curves used to describe the ship course and velocity.

Szapczynska et al. (2009) also proposed a multi-criteria evolutionary weather-routing algorithm. The framework in the proposed algorithm is a normal genetic-algorithm-iterative process of population development, resulting in a Pareto-optimal set of solutions. The initialization of the objective to be optimized is four routes: an orthodrome, a loxodrome, a time-optimized isochrone route and a fuel-optimized isochrone route. Specialized operators are used for evolution, including a one-point crossover, a non-uniform mutation, and route smoothing by means of average weighting.

Vettor (2016) introduced a ship route optimization algorithm that uses the strength Pareto Evolutionary Algorithm to approximate the most favourable set of solutions for route optimization. The objectives to be optimized are two sets of variables, one for the ship's position and the other for its speed. It uses Dijkstra's algorithm to generate the initial population. This can guarantee that each of the individuals in the population is a feasible solution for a ship route. However, the variation of the route is based on the prefix grid system by the genetic algorithm, which leads to question if the implementation of the genetic algorithm is indispensable.

Path-finding algorithm

Padhy (2007) proposed to utilize Dijkstra's algorithm (Dijkstra, 1959) to solve the ship routing problem. The proposed method uses a grid formed by latitude and longitude lines, and the speed is based on a given engine setting. The weight functions for nodes and the routes are determined by considering both involuntary and voluntary speed reductions. The edges of the graph are weighted by transit time. The author notes that Dijkstra's algorithm is very versatile and can be applied to the ship routing problem. Further improvements can be made to his work, such as improving the grid system, since the rectangular grid constrains the ship's heading, which probably increases the cost by frequently changing course.

Roh (2013) proposed a method for determining an economical route for a ship based on the acquisition of the sea state. The method is based on the A* algorithm (Hart, 1968), which combines Dijkstra's algorithm and the greedy algorithm. The difference between the A* algorithm and Dijkstra's algorithm is that a heuristic function is contained in the A* algorithm. The heuristic function helps the algorithm find the target faster than Dijkstra's algorithm. However, the heuristic function is not shown in the Roh paper, and the square grid system is not suitable for route optimization.

Veneti (2017) presents an improved solution to the ship weather routing problem based on an exact time-dependent bi-objective shortest path algorithm that attempts to optimize two different conflicting objectives: fuel consumption and risk along the route. It creates a static square grid graph between the departure point and destination with static information such as geographic and bathymetric information and a dynamic grid, which contains weather and sea conditions and updates itself when new data are available.

1.3 Motivation and objectives

Different voyage optimization algorithms may provide different optimization results. Even for the same algorithm, different parameter settings can give diverse optimization results. It is essential to identify the optimization uncertainties, the advantages and particularly the disadvantages of current voyage optimization algorithms. For example, a drawback of the dynamic programming method is that when using a pre-defined geometrical grid/waypoint system, the solution of an optimal route may end up with too frequent (unrealistic) course changes. In practice, it may increase the ship operators' navigation effort and fuel consumption. Thus, analyses and comparisons of these conventional voyage optimization algorithms are imperative. It is also important to investigate the capabilities and efficiency of different optimization algorithms for various voyage optimization objectives, such as the expected time of arrival, minimum fuel cost and low crack propagation in ships, etc.

Furthermore, conventional voyage optimization algorithms begin each iteration in the optimization process by fixing a locally optimal solution (that enters the next iteration as a parent node). Because generated nodes are dependent on previous locally optimal nodes, the final solution composed of a number of locally optimal nodes can hardly be a globally optimum route. It means that conventional can only generate globally optimal routes for ship voyage planning under very strict conditions, e.g., a ship has to sail at a fixed speed along an entire voyage. These conditions cannot be fulfilled for most ship navigations, in particular for ocean crossing voyages. On the other hand, an evolutionary algorithm may have the potential to provide globally optimal routes for route planning. But even for a simple voyage optimization problem that changes only geometrical variables (longitude and latitude), the search space for finding an optimum route in this algorithm grows exponentially as the number of elements (e.g., discretized sailing stages and pre-defined waypoints at each stage, etc.) increases. Hence, for actual voyage optimization that has to contain two sets of dependent variables, i.e., a geometrical waypoint assigned with certain sailing speeds, it is nearly impossible for any evolutionary algorithm to find an optimum solution. Thus, for actual ship voyage optimization, a novel algorithm should be developed that can overcome the limitations of both conventional voyage optimization algorithms and evolutionary algorithms. In particular, this voyage optimization algorithm should be able to generate globally optimal voyage routes without costing much computational effort.

Therefore, the objective of this thesis is to develop a novel voyage optimization algorithm based on the benchmark study, which is used to investigate the pros/cons of state-of-the-art voyage optimization algorithms and their capabilities for voyage optimization objectives of, e.g., expected time of arrival, minimum fuel cost and lower crack propagation in ship structures, etc. This new optimization algorithm should inherit the advantages of current voyage optimization algorithms while overcoming their limitations. Thus, it should be able to provide a globally optimum objective

solution (i.e., minimize the negative impact of multi storm weather conditions along a whole voyage) and solve the multi-objective optimization problem for voyage planning. To achieve the overall objective, the following tasks were performed in this thesis work:

- a. Compare the most commonly used voyage optimization algorithms to provide a fair summary of their advantages and disadvantages and investigate the impacts/benefits of implementing these voyage optimization algorithms for optimum route planning with respect to fuel saving, accurate expected time of arrival, etc.
- b. Demonstrate the capabilities and benefits of using various voyage optimization algorithms to mitigate the risk of overly rapid crack propagation in ship structures, and study the potential extension of sailing life with the help of conventional voyage optimization systems.
- c. Propose a better hybrid optimization algorithm that shares the benefits of both Dijkstra's algorithm for three dimensional globally optimum path-finding and the Genetic algorithm for local speed refinement, and compare the potential benefits of implementing this hybrid algorithm for multi-objective route planning, i.e., fuel saving and expected time of arrival.

1.4 Outline of the thesis

Chapter 2 describes the methodology and details of the routing optimization algorithms, the ship performance model used in these algorithm as well as the limitations of the research. A brief summary of results drawn from Papers I, II, and III is presented in Chapter 3. The conclusions of the thesis work are summarized in Chapter 4. Plans for future work are presented in Chapter 5.

2 Methods and models in a voyage optimization system

Modern voyage optimization systems are used in today's vessels to plan their sailing schedules based on a 7-14 day weather forecast, e.g., GAC-SMHI (2018) and Storm Geo (2018). The weather forecasts of MetOcean conditions contain large uncertainties, particularly for forecasts longer than 3 days. Therefore, voyage optimization systems often request forecast information from multiple weather providers, e.g., from different metrological institutes with their own weather models, satellites or in situ measurements. In addition to the MetOcean forecast information, an optimum routing plan for a specific voyage must also rely on robust voyage optimization algorithms, and on certain models to describe a ship's performance, e.g., fuel consumption rate, sailing speeds, and fatigue accumulation, (referred to ship performance models here). Requirements for the ship performance models are determined from the pre-defined objectives for the voyage optimization. Since the focus of this study was to investigate the capabilities of voyage optimization algorithms, the required MetOcean forecast information, e.g., significant wave height, wave period, and wind speed, were extrapolated from the ERA Interim hindcast data (Dee et al., 2011). The dataset has six hours' time and 0.75 degree grid resolution, and was downloaded from the ECMWF (European Centre for Medium-Range Weather Forecasts). The ocean current information was accessed from the server https://podaac.jpl.nasa.gov/dataset/OSCAR_L4_OC_third-deg. These weather datasets are assumed to have been the ground-truth MetOcean conditions encountered by our case-study ships.

To demonstrate various optimization algorithms for optimum route planning with different objectives, we have adopted three objectives as case studies: Expected Time of Arrival (ETA), minimum fuel cost and lowest fatigue-crack propagation. To achieve these objectives, the optimization process needs the ship's speed-power performance models that describe the ship's sailing speeds in terms of weather conditions encountered and ship status and fatigue-crack-propagation models that describe how quickly a fatigue crack grows under various operational and weather conditions. It should be noted that for this study, both models were implemented from well-established theorems and formulas. For completeness, the following Section 2.2 briefly presents the two ship performance models used in our optimization approaches. Various state-of-the-art voyage optimization algorithms and their implementations in this study are presented in Section 2.3.1. Section 2.3.2 describes in detail a hybrid Dijkstra and Genetic algorithm we propose to allow multi-objective and speed-varying voyage optimization. Finally, Section 2.4 presents the assumptions and limitations of current voyage optimization algorithms.

2.1. Mathematical definition of general voyage optimization problem

A ship's sailing route is defined as shown in Fig.2 by a series of waypoints $\vec{P}$ (forming a ship's trajectory) and their associated times of passing time. The waypoints and times can be used to calculate the series of the ship's operational conditions, $U(\vec{P})$, i.e., sailing speeds and headings along the route. In this study, for a simple description of our optimization algorithm, the variables used to define a ship's sailing route are denoted as follows:

- Ship state variable: $\mathbf{P} = [x, y, t]^T$ where x, y, t represent longitude, latitude and time, respectively.

- Ship control variable: $\mathbf{U}(\mathbf{P}) = [v, \theta]^T$, where v is the ship velocity and θ is its heading angle to form a ship's operational condition in one ship state $\mathbf{P}$.
- Weather conditions: $\mathbf{W}(\mathbf{P}) = [H_s, T_p, C, V_{wu}, V_{wv}, \dots]^T$ representing ocean waves $[H_s, T_p, S_w(H_s, T_p)]$, current C , and wind parameters $[V_{wu}, V_{wv}]$, etc., for a ship state $\mathbf{P}$.
- Ship sailing constraints: $\mathcal{C}(\vec{\mathbf{P}}, \mathbf{U}(\vec{\mathbf{P}}))$, which include ship sailing constraints such as geometric constraints, control constraints (land crossing constraints, marine engine power constraints, etc.). The function returns a Boolean value that indicates the feasibility of the sailing conditions, i.e., $\vec{\mathbf{P}}$ and $\mathbf{U}(\vec{\mathbf{P}})$.

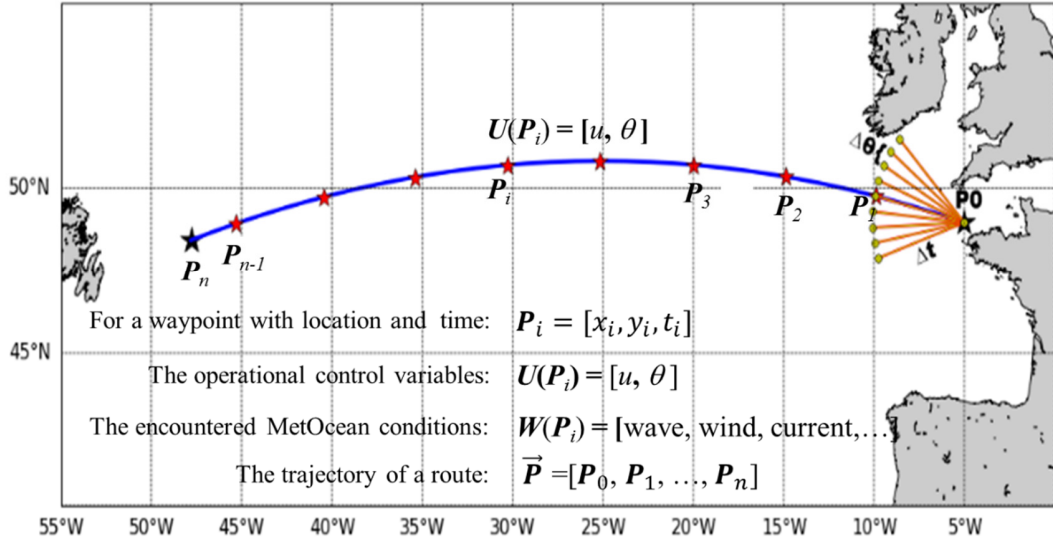


Fig. 2. An illustration of the trajectory of a ship route by its waypoints and operational conditions

For different ship operation strategies used in worldwide shipping companies, such as a constant speed or fixed engine power/RPM (revolutions per minute) operation, the above ship control variables may differ significantly in routing optimization algorithms.

Under the constraint $\mathcal{C}(\vec{\mathbf{P}}, \mathbf{U}(\vec{\mathbf{P}}))$, the objective function J can be denoted by:

$$J = \int_{t_s}^{t_e} f(\mathbf{U}(\vec{\mathbf{P}}), \mathbf{W}(\vec{\mathbf{P}})) dt \quad (1)$$

where $f(\mathbf{U}(\vec{\mathbf{P}}), \mathbf{W}(\vec{\mathbf{P}}))$ is the instantaneous cost function (ship performance models) for a series of ship states $\vec{\mathbf{P}}$ under control $\mathbf{U}(\vec{\mathbf{P}})$; t_s, t_e are the departure and arrival times, respectively. Here, the objective function of a route plan can be of different forms, e.g., fuel consumption, maximum ship motions, estimated time of arrival (ETA), fatigue damage accumulation, and crack propagation in a ship's structure (Wang et al., 2018).

Depending on optimization methods, the total cost function in Eq. (1) can be divided into various discrete stages. The instantaneous cost functions f may be different objectives (e.g., fuel consumption, expected time of arrival, and fatigue damage accumulation) in the optimization

algorithms. Finally, the overall objective for an optimum voyage plan is to find suitable waypoints $\vec{P}$ and operational control sets $U(\vec{P})$ that will lead to the minimum/maximum value of J due to optimum planning for sea conditions $W(\vec{P})$ encountered at those waypoints.

2.2. Ship performance model

Ship performance models describe a ship's performance, e.g., sailing speed (Kwon 2008), motion/damage response (Mao 2014), and fuel cost (Tillig 2017), in terms of its loading conditions, encountered weather conditions, and operational conditions. These models are the core elements in a voyage optimization process to estimate the cost function for specific objectives. The ship fuel consumption model describes a ship's speed and engine power relationship as a function of the ship's main dimensions, status and sea conditions. The fatigue crack propagation model is used to predict the crack propagation rate in the ship structures using the above information (Mao 2014).

2.2.1 Fuel consumption model

The energy-transfer system in a ship is complex (Tillig 2017) and contains many components, such as the ship resistance and hull efficiency. To describe a ship's speed-power relationship, the most important component is to accurately estimate a ship's resistance in different conditions (Kwon, 2008). Ship resistance can be divided into three parts, calm water resistance, added resistance due to waves and added resistance due to wind. Calm water resistance is one of the most important parts in describing a ship's resistance. Its proportion to the total resistance will eventually determine the choice of ship route by the routing optimization algorithm chosen. Since weather and sea conditions are the main factors in weather routing problems (Bowditch, 2002), an accurate model for estimating the added resistance due to waves is thus an important input for a weather routing system. When sailing in severe sea conditions, e.g., significant wave height larger than 5 metres, added resistance due to waves will lead to a significant reduction of ship speed for the same engine power consumption. Finally, added resistance due to wind is relatively small but also crucial due to the direction of the wind for determining the heading angle in a voyage.

The workflow for the ship speed-power prediction used in this thesis is presented in Fig. 3. It is a typical estimation procedure to predict the fuel consumption rate using input parameters of encountered weather information, the ship's characteristics, operational profiles, etc. This procedure has been implemented into an in-house code using the following mathematical formulas.

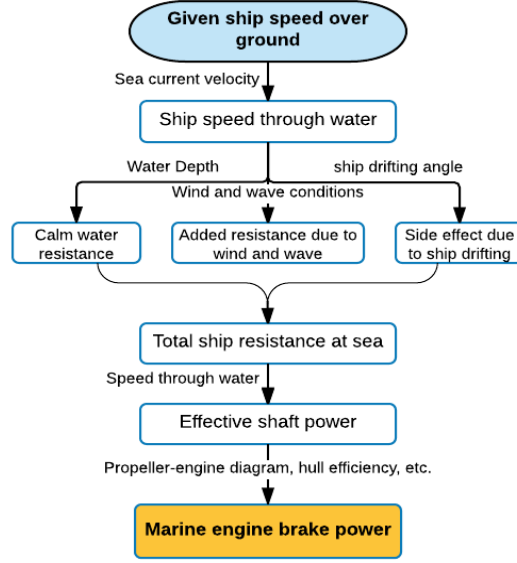


Fig. 3. Ship speed-power prediction flowchart for routing optimization

Mathematically, for a sailing state at the waypoint P_i of $U(P_i)$ in a stationary sea state $W(P_i)$, (lasting from 20 minutes to 6 hours, here using 3 hours), a ship's fuel consumption can be estimated by:

$$FC = P_b \times c_{sfoc}, \quad P_b = \frac{R_{tot} \cdot v_i}{\eta_0 \cdot \eta_h \cdot \eta_s} \quad (2)$$

where c_{sfoc} is the specific fuel oil consumption, η_h , η_0 , η_s are the hull efficiency, propeller open water efficiency, and engine shaft efficiency, respectively, v_i is the ship speed and R_{tot} is the total ship resistance in the state. It is a function of ship operational conditions U and sea conditions W at the sailing waypoint, i.e., $R_{tot} = f(U(P_i), W(P_i))$. The specific fuel oil consumption and the three efficiencies in Eq. (2) can be regarded as fixed for the route optimization of a specific voyage. In general, the ship's total resistance R_{tot} , it can be decomposed in accordance with the following equation:

$$R_{tot} = R_T + R_{AW} + R_{AA} \quad (3)$$

where R_T is the calm water resistance; R_{AW} is the add resistance due to wave; R_{AA} is the wind resistance.

Calm water resistance

The calm water resistance R_T may be calculated by the Holtrop-Mennen (1983) method viz:

$$R_T = (1 + k)R_F + R_W + R_{APP} + R_A + R_B \quad (4)$$

where:

k Frictional resistance correction factor,

R_F	Frictional resistance,
R_W	Wave-making and wave-breaking resistance,
R_{APP}	Additional resistance,
R_A	Roughness allowance and still air resistance
R_B	Resistance due to the bulbous bow

In the Holtrop-Mennen method, the above items are computed by empirical formulas in terms of, e.g., a ship's main dimensions, ship type, the dimensions of the bulbous bow and immersed transom, etc. Those formulas are derived based on a large number of model tests and can give a rough estimate of a ship's calm water resistance.

Added resistance due to wave

The added resistance R_{AW} due to waves is often divided into two components, i.e., the added resistance due to wave reflections R_{AWR} and the added resistance due to ship motions at sea R_{AWM} :

$$R_{AW} = R_{AWR} + R_{AWM} \quad (5)$$

These two items can be estimated by either numerical calculations or experimental tests. In both approaches, a ship's added resistance at regular waves of various frequencies with unit amplitude (i.e., the so-called resistance Response Amplitude Operators RAOs) is obtained. For the added resistance at a specific sea state ($[H_s, T_p, S_w(H_s, T_p)]$), the RAOs are multiplied with the encountered wave spectrum S_w and integrated along the whole frequency range to obtain the added resistance in waves at the specific sea condition. In this study, the empirical formulas proposed by Liu (2016) is used to estimate a ship's wave resistance to demonstrate the capability of various algorithms for ship voyage optimization.

Added resistance due to wind

The resistance increase due to wind can be calculated according to ISO 15016:2015(E) by the formula below:

$$R_{AA} = 0.5\rho_A \cdot C_{AA}(\Psi_{WRref}) \cdot A_{XV} \cdot V_{WRref}^2 - 0.5\rho_A \cdot C_{AA}(0) \cdot A_{XV} \cdot V_G^2 \quad (6)$$

where:

R_{AA}	is the resistance increase due to relative wind;
A_{XV}	is the transverse projected area above the waterline including superstructures;
C_{AA}	is the wind resistance coefficient; $C_{AA}(0)$ means the wind resistance coefficient in head wind;
V_G	is the measured ship's speed over ground;
V_{WRref}	is the relative wind velocity at the reference height;
Ψ_{WRref}	is the relative wind direction at the reference height;
ρ_A	is the mass density of air.

The theoretical methods presented above contain large uncertainties, and the estimated fuel consumption may differ significantly from a ship's actual fuel cost, particularly if the added

resistance in waves is taken into account; see, e.g., Tillig (2017) and Mao (2016). In this study with two case-study vessels with a large volume of full-scale energy performance data available, the machine-learning method was used to describe the difference between the estimated and measured costs as in Mao et al. (2016). Furthermore, another ship performance model (relationship between ship speed and the engine RPM) was derived using solely statistical regression methods for the investigation of the routing optimization of a container ship, Mao et al. (2017).

2.2.2 Fatigue propagation model

For practical engineering application, the fatigue crack propagation estimation is mainly based on the Linear Elastic Fracture Mechanics (LEFM), e.g., Anderson (2017), Sumi (1998), etc. In this study, the LEFM is implemented with a ship's spectral response analysis. It yields a simple but reliable fracture model for crack growth analysis in ship structures. The detailed derivation of the model can be founded in Mao (2014). In the following, some basic equations used in this study are briefly described. First, a ship's fatigue damage is mainly caused by the continuously varying wave loads acting on ship structures. The random motions of ocean waves causes the variation of wave loads acting on ship structures. The stress response in the frequency domain can be estimated by the wave spectrum and RAOs for any arbitrary sea state characterized by significant wave height H_s , wave period T_z , and wave spectrum S_w .

Calculation of wave load in a stationary sea state

For ship structural fatigue analysis, ship stress response along a ship route, i.e., $\vec{P}$ and $U(\vec{P})$ here, is often divided into a series of stationary periods of weather information, $W(\vec{P}) = W_1, W_2, \dots, W_n$. A sea state W is described by a classical wave spectrum $S(\omega)$, i.e., Pierson-Moskowitz or JONSWAP, which is a function of significant wave height H_s and wave period T_z shown in Fig.4. The transfer function or response amplitude operators (RAOs) of structural stresses is obtained for various ship speeds and heading angles $U = [v, \theta]^T$. It is denoted by $H_\sigma(\omega|v, \theta)$ shown in Fig.4.

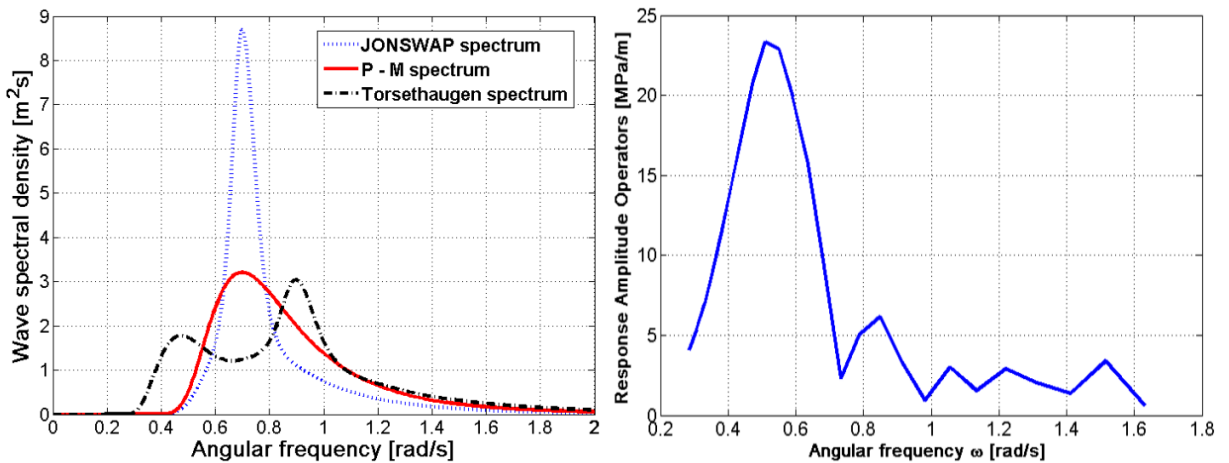


Fig. 4. Three typical wave spectra Stress and RAOs of a deck longitudinal stiffener

The stress is often assumed to be Gaussian and is uniquely defined by its mean value and spectrum. For a specific sailing speed U and heading angle θ , the stress response spectrum under arbitrary sea states can be computed by:

$$S_x(\omega|v, \theta, H_s, T_z) = |H_x(\omega|v, \theta)|^2 S_e(\omega|H_s, T_z) d\omega \quad (7)$$

where $S_e(\omega|H_s, T_z)$ is the encountered wave spectrum, which cannot always be expressed explicitly for all wave frequencies. Instead it is sufficient to only obtain the spectral moments of the ship response for a ship's structural integrity assessment. The n th order spectral moments can be calculated by:

$$\lambda_n = \int_0^\infty \left| \omega + \frac{\omega^2 v \cos \theta}{g} \right|^n H_x^2(\omega|v, \theta) S(\omega|H_s, T_z) d\omega \quad (8)$$

Fatigue crack propagation model

The crack propagation analysis is based on the linear elastic fracture mechanics (LEFM) using the stress intensity factor (SIF) K . For most ship steel materials, the crack growth rate da/dN against the SIF range ΔK on log-log scales looks like a sigmoidal curve as in Fig.5.

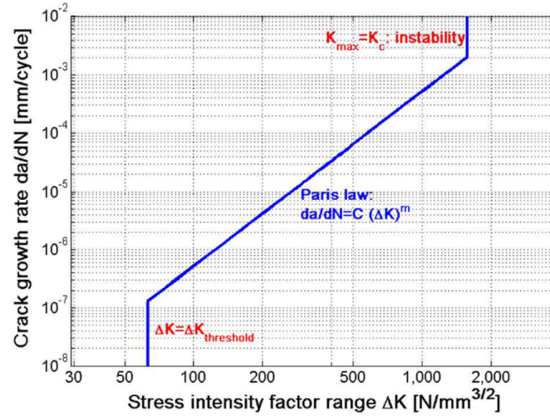


Fig. 5. Simple fatigue crack growth relationship (BS 7910, 2005)

The fatigue crack propagation predicted by the Paris law can be written as:

$$\frac{da}{dN} = C \cdot \Delta K^m \quad (9)$$

where a is the crack length, C and m are material parameters that can be got from design rules, e.g. BS 7910 2005., ΔK is the SIF range during a stress cycle, and da/dN is the corresponding crack growth rate.

For ship structures composed of shell and beam elements, the mode I crack is the most common case. This thesis is limited to this mode using LEFM principles. Thus, the SIF can be written as:

$$K = S \cdot f\left(\frac{a}{w}\right) \sqrt{\pi a} \quad (10)$$

where S is the stress perpendicular to the crack plane, w is the width of the crack plane, and $f\left(\frac{a}{w}\right)$ is a dimensionless parameter in terms of the crack geometry and type of loading; see Mao (2014). To predict the fatigue crack propagation due to variable amplitude stresses, fast and reliable spectral method proposed by Mao (2014) is used for the crack analysis. Let $S(t)$ denote the variable amplitude stresses in ships and $g(a) = f\left(\frac{a}{w}\right) \sqrt{\pi a}$ be the stress intensity coefficient here. The crack increment at time t is approximated by:

$$da(t) \approx C \cdot g^m(a(t)) \cdot m \cdot \dot{S}^+(t) (S^+(t))^{m-1} dt \quad (11)$$

where $S^+ = \max(0, S)$. The Eq. (11) is derived by assuming that the crack increment per cycle is small, as the parameter C is very small, while the number of stress cycles in a sea state here is less than a few hundreds. It is actually an upper bound of the crack increment for the variable amplitude stresses. For ship fatigue assessment, the stress response in a stationary sea state is often assumed to be narrow band Gaussian processes. Then, the expected crack increment under the i th sea state $t \in [T_i, T_{i+1}]$ is computed by:

$$E[\Delta a_i] = C \cdot g^m(a_i) \cdot \frac{\Delta T}{2\pi} \sqrt{\frac{\lambda_2}{\lambda_0}} \Gamma\left(\frac{m}{2} + 1\right) \cdot (2\lambda_0)^{\frac{m}{2}} \quad (12)$$

where $g(a)$ can be computed from a fracture mechanic program, e.g. FRANC2D by Wawrzynek and Ingraffea (1991), ΔT is the time interval for a stationary sea state of $\Delta T = T_{i+1} - T_i$, $\Gamma()$ is the gamma function, λ_0 and λ_2 are the zero- and second order of the spectral moments of the stress $\sigma(t)$ for $t \in [T_i, T_{i+1}]$. The values of λ_0 and λ_2 can be computed by Eq. (8) for ship fatigue assessment.

2.3. Voyage optimization algorithms

First, a summary of conventional optimization algorithms used for ship route planning is presented, and their drawbacks and connections are also briefly discussed. This summary provides information regarding the state-of-the-art optimization algorithms for weather routing research and innovation. Then, a hybrid routing optimization algorithm is proposed to consider multi-objective optimization and three-dimensional ship navigation/operation parameters control, i.e., varying ship speed and waypoints for globally optimized route planning.

2.3.1 Conventional routing optimization algorithms

The conventional routing optimization algorithms studied in paper I can be categorized into two types, dynamic grid based methods and static grid based methods. Dynamic-grid-based methods, which include the Isochrone and Isopone methods, generate nodes in every optimization iteration. Static-grid-based methods include dynamic programming, 3D dynamic programming and Dijkstra's algorithm; in these, the optimization is based on a pre-defined graph or grid system. The relationship between the two types can be summarized as in Fig. 6.

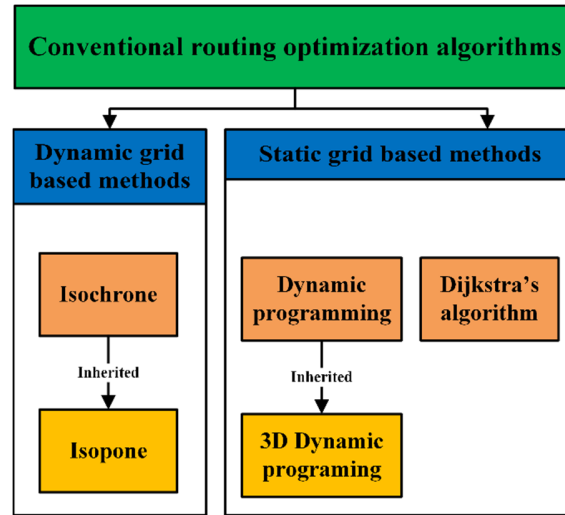


Fig. 6. Relationship of routing optimization algorithms

2.3.1.1 Dynamic grid-based methods

Here, the Isochrone method is taken as an example to illustrate the dynamic-grid-based methods. It regards the instantaneous cost function $f(\mathbf{U}(\vec{\mathbf{P}}), \mathbf{W}(\vec{\mathbf{P}}))$ in Eq. (1) as the objective to be minimized. The Isochrone method treats the optimization problem in Eq. (1) as a multi-stage decision process by discretizing the whole voyage into a series of time intervals (sea states/waypoints $\vec{\mathbf{P}}$). Thus, the discrete optimization problem of finding an optimal route $\vec{\mathbf{P}}^*$ is reduced to determining an optimal control variable $\mathbf{U}(\vec{\mathbf{P}}^*)$ that minimizes function f of waypoint $\vec{\mathbf{P}}^* = [\mathbf{P}_1^*, \mathbf{P}_2^*, \dots, \mathbf{P}_N^*]^T$, $\mathbf{U}(\vec{\mathbf{P}}^*) = [\mathbf{U}_1^*, \mathbf{U}_2^*, \dots, \mathbf{U}_N^*]^T$. The control variable $\mathbf{U}(\vec{\mathbf{P}}^*)$ in the Isochrone method has two parameters, ship speed and heading angle. To find the optimal control variable $\mathbf{U}(\vec{\mathbf{P}}^*)$ and keep computational effort minimal, this method fixes the speed and varies the heading

angles, i.e., $\vec{P}^*$. The heading angles at each potential position are created by discretizing the heading angles in each stage with a fixed angle interval, e.g., as shown in Fig. 7. The implementation of the method can be summarized as the following steps.

Table.1. Implementation of the Isochrone method

1	Let a ship depart from sailing with a series of discretized headings, $\theta_0 \pm i \Delta \theta$ ($i = 0, 1, \dots, m$), where θ_0 is the initial course of the great circle from departure to destination and $\Delta \theta$ is the increment of heading. After sailing for a fixed time Δt , the ship reaches its first isochrone stage with nodes/waypoint represented by $P_{1,j}$, $j = 1, 2, \dots, 2m + 1$. Note that $2m$ sub-sectors Δs_i , $i = 1, 2, \dots, 2m$, along the reference route will be created to the destination as in Fig. 7.
2	Let the ship depart from each waypoint $P_{1,j}$ of the first stage $t_1 = \Delta t$. As in Step 1, the ship will sail at discretized headings $\theta_1 \pm i \Delta \theta$ ($i = 0, 1, \dots, m$), where θ_1 is the arrival heading of the great circle from departure to $P_{1,j}$.
3	Select one node/waypoint in each subsector Δs_i (where i is the stage number shown in Fig. 7) to be the candidate parent waypoint for the iteration of the next time stage.
4	Repeat steps 2 and 3, until it reaches the destination.

The most controversial issue in the optimization process is step 3. The node-selection method can be interpreted as the way of choosing a candidate parent node from subsectors. It has a large influence on the resulting the optimal route. The criterion to choose candidate waypoints for each sub-sector can be, e.g., longest distance from departure, shortest distance from destination, and lowest cost.

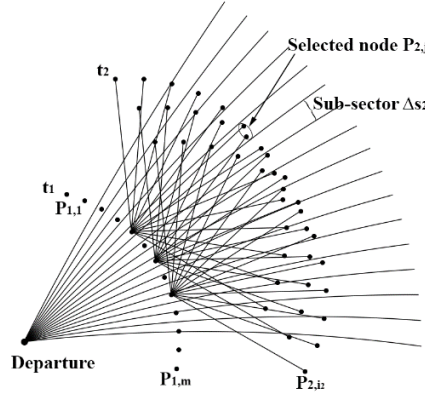


Fig. 7. Sub-sectors and node selection

2.3.1.2 Static grid-based methods

Static grid-based methods first generate a waypoint grid or path graphs around a ship's sailing region. In conventional voyage optimization methods, the generated waypoint grid system is a two-dimensional path graph of longitude and latitude waypoints between the departure and the destination, as shown in Fig. 8. According to De Wit (1990), the grid is generated based on the great circle reference route. It is composed of a series of stages that contain waypoints perpendicular to the great circle route. This waypoint grid system provides a good approximation

of the actual route. The pre-defined waypoint grid system should cover the entire region into which it is possible a ship may need to sail.

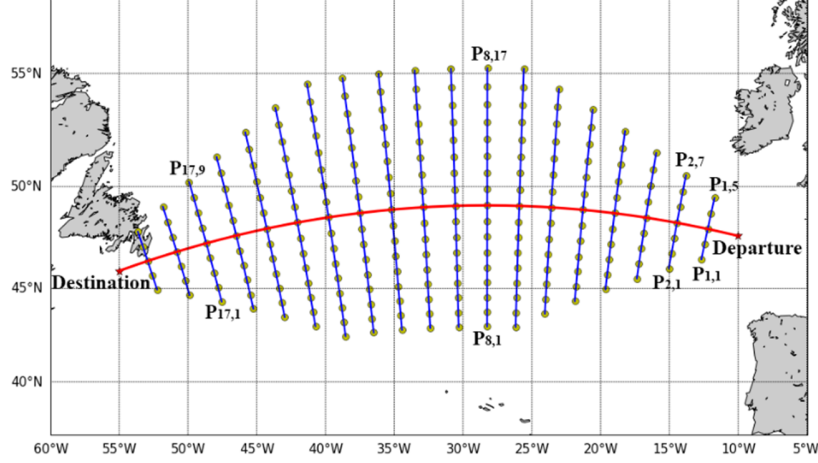


Fig. 8. Pre-defined grid system

Dynamic programming

Based on Bellman's Principle of Dynamic Programming (Bellman, 1952), an optimal route must satisfy the following condition: "an optimal policy has the property that whatever the initial state and initial decision is, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision". As demonstrated in Fig. 8, let $\mathbf{G}$ be a waypoint grid system from departure point $\mathbf{P}_0$ via nodes $\mathbf{P}_{1,i_1}, \mathbf{P}_{2,i_2}, \dots, \mathbf{P}_{m-1,i_{m-1}}$ to destination $\mathbf{P}_m$, where i_n is the chosen waypoint/node index at the n -th stage of the optimized route.

For the implementation of the Dynamic programming method, let $\mathbf{CP}_{i,j}$ denote all costs (e.g., fuel consumption, damage accumulation, and time) that a ship incurs sailing to node $\mathbf{P}_{i,j}$ from all waypoints of the preceding stage. Assume that there are n waypoints at each stage. Denote the cost for the ship to sail from the k -th waypoint $\mathbf{P}_{i-1,k}$ of the preceding stage to the current waypoint $\mathbf{P}_{i,j}$ as Δc_k and the required time of sailing as Δt_k . The costs at node $\mathbf{P}_{i,j}$ are:

$$\mathbf{CP}_{i,j} = \begin{bmatrix} cp_{i-1,1} + \Delta c_1 \\ \vdots \\ cp_{i-1,n} + \Delta c_n \end{bmatrix} \quad (13)$$

where $cp_{i-1,k}$ is the cost that a ship incurred to sail to the point $\mathbf{P}_{i-1,k}$, while $\Delta \mathbf{c}_k$ is the instantaneous cost calculated by Eq. (1):

$$\Delta c_k = f\left(\mathbf{U}(\mathbf{P}_{i-1,k}), \mathbf{W}(\mathbf{P}_{i-1,k})\right) \Delta t_k \quad (14)$$

Based on the basic dynamic programming principles, the minimum of these n costs in Eq. (13) is chosen as the optimal sub-path to reach the point $\mathbf{P}_{i,j}$. Following the same approach, the optimal sub-paths of minimum costs for all other nodes in the same i -th stage as $\mathbf{P}_{i,j}$ can be found. Subsequently, the minimum-cost sub-path from departure to the i -th stage is memorized. Repeating

this procedure until reaching the destination point, the minimum-cost optimal ship route in the grid system can be generated.

Dijkstra's algorithm

Dijkstra's algorithm operates in a waypoint grid/graph system by visiting sub-paths/edges starting from the departure node/waypoint. It follows two basic principles (Dijkstra 1959): first, a sub-route of a shortest route is itself a shortest route, and second, with a given shortest distance x , between points A and C , a path going from point A to C through a third point B will always be of a distance greater than or equal to x .

Fig. 9 illustrates Dijkstra's algorithm for finding the minimum cost path from the Point a to the Point i . The costs for traversing sub-paths are marked in each sub-path. For a specific node/waypoint, the algorithm searches for all possible sub-paths that can lead to the node, and only the one with minimum cost will be recorded while the other possible sub-paths are eliminated from the search system. For example, to reach point d , Dijkstra algorithm will search for all possible sub-paths, i.e., $a-b-d$, $a-d$, and $a-c-d$, whose costs are 4, 7 and 8, respectively. Hence, the first sub-path, i.e., $a-b-d$, is kept and associated with the point d . Continuing the process until reaching point i , the whole optimum route will be found.

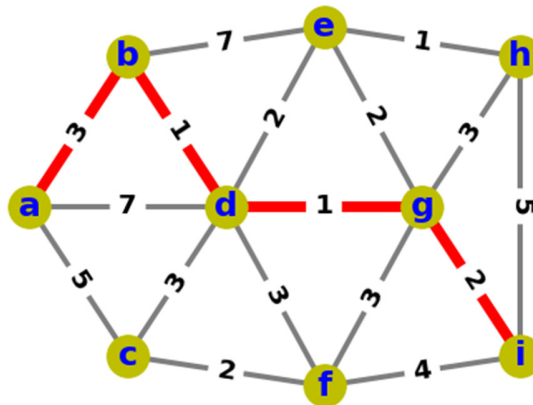


Fig. 9. Illustration of the Dijkstra algorithm.

2.3.1.3 Analysis of conventional voyage optimization algorithms

The Isochrone method has been widely used for route-optimization problems with stricter ETA requirements (Hagiwara 1989), such as in Line Shipping companies. It uses an iterative procedure to generate a grid and simultaneously search optimal solutions. The grid generated by the Isochrone method is much more flexible than those of other methods because many factors can affect the iterative calculation procedure and directly influence the grid generation. For example, by lowering the time interval in each stage, the quality and accuracy of the results can be increased, but the computational effort is also increased. As mentioned above, another issue that can greatly influence the results is the method of node selection. Changing the selection method can yield different Isochrone fronts for stages and consequently yield different optimization results. If the topography is complex, the Isochrone method can be unstable because all the Isochrone nodes may pin up on

land and calculation iterations might not be able to proceed. In summary, the Isochrone method is less stable than the methods employing predefined grid systems.

Static grid-based methods search for an optimum ship route based on predefined waypoint grid systems. The optimization procedure for static-grid-based methods can be divided into two steps: create the waypoint grid system around the ship's sailing area, and implement a path/waypoint search method to pick candidate sailing routes based on specific objective functions. Theoretically, for the same grid system, the results given by different static grid-based methods can be quite similar to each other. Thus, the quality/resolution of a pre-defined waypoint grid system is the key factor in determining the efficiency of this voyage optimization method. By increasing the resolution of the grid system, the voyage optimization solutions can be improved, while the computational effort of the optimization process will also be significantly increased. Additionally, predefined grid systems can be easily used to model sailing areas with complex topography, e.g., sailing along the coast, or sailing in channels.

2.3.2 Hybrid routing optimization algorithm

To allow for multi-objective voyage optimization that can exploit voluntarily changes to a ship's speed/power inputs along various sailing stages in the optimization process, a hybrid routing optimization algorithm (HROA) was proposed in Paper III. It uses general optimization algorithms for the routing plan: Dijkstra's algorithm and the genetic algorithm. An overall description of the proposed HROA is presented in Fig. 10.

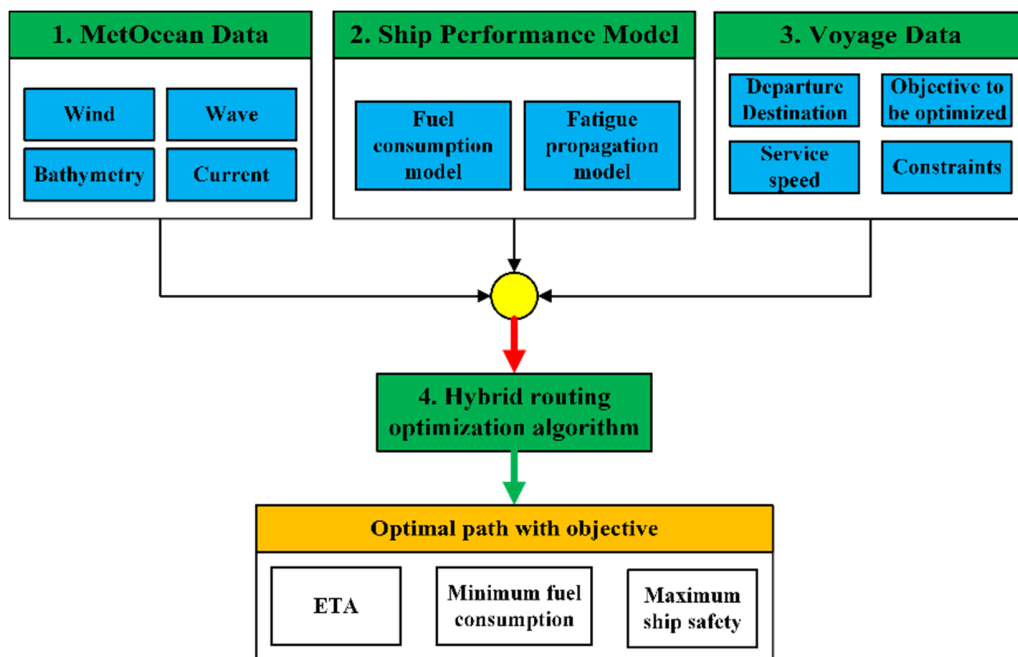


Fig. 10. Overall structure of ship routing optimization

The optimization process contains four basic components/models:

1. MetOcean data describes the sea conditions that the ship will encounter;
2. The ship model predicts a ship's energy performance;
3. Voyage data captures information from the users, such as objectives that need to be optimized and service speed.
4. Finally, the HROA is used to generate an optimum routing schedule with all waypoints and associated passing times. The scheme of the HROA is presented in Fig. 10. First, a static 3D weighted path-graph system composed of waypoints (i.e., represented by longitude, latitude and time) is created/pre-defined. Then, the Dijkstra algorithm is used to construct an initial candidate optimum route based on the pre-defined path-graph system and required objectives. Finally, the genetic algorithm is employed to refine the initial route to generate a globally optimum ship route. Additional details are presented below.

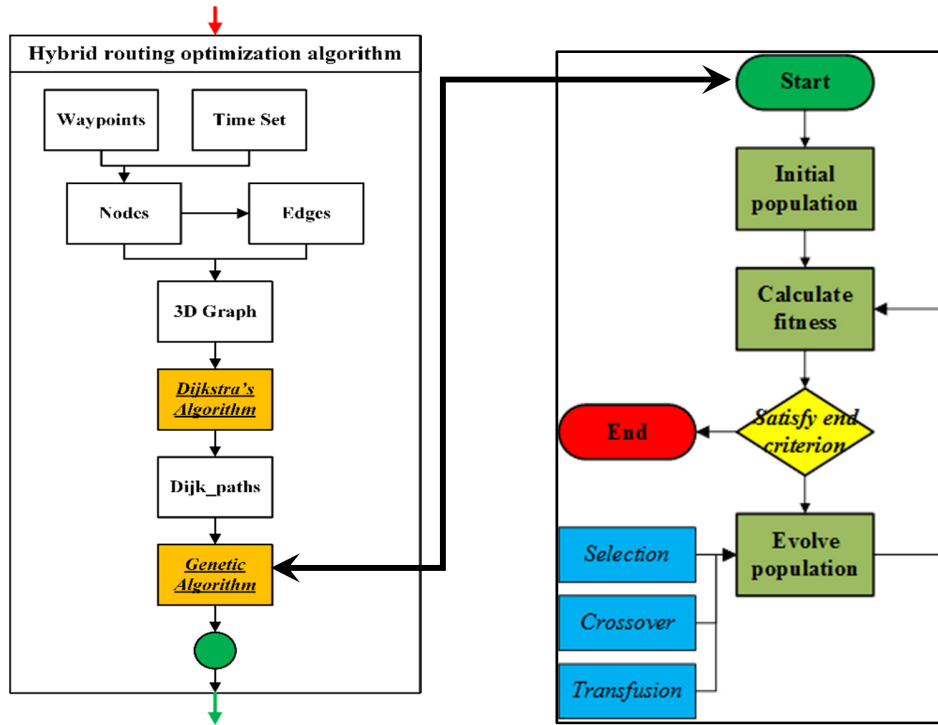


Fig. 11. Proposed hybrid optimization approach combining Dijkstra and Genetic algorithms

Dijkstra's algorithm: generation of initial ship route

For a practical ship route optimization, a voyage should be first discretized into various stages to construct a waypoint grid/path-graph system $G = (\vec{P}, \vec{A})$, where $\vec{P}$ is a set of pre-defined waypoints/nodes, and $\vec{A}$ is a set of sailing paths/edges composed of pairs of waypoints/nodes that are ordered in certain ways. The path-graph system is often based on the great circle reference route between the departure and destination points of the voyage as shown in Fig. 8. Every sailing sub-path is assigned with a weight. Assume that $\vec{A}_j$ is the sub-path/edge connecting nodes P_{j-1} and P_j , and the time cost is Δt_j ; according to Eq. (1) the weight of the edge becomes:

$$CP_j = f\left(\mathbf{U}(\mathbf{P}_{j-1}), \mathbf{W}(\mathbf{P}_{j-1})\right) \Delta t_j \quad (15)$$

In this optimization problem, a node/waypoint $\mathbf{P}$ is defined as the geographical location (longitude and latitude) and expected time of arrival at the waypoint. The sub-path/edge is defined as the connection of two nodes/waypoints from adjacent stages.

In more detail, the three-dimensional discretization of the voyage $\mathbf{G} = (\vec{\mathbf{P}}, \vec{\mathbf{A}})$ is conducted in two different steps. As shown in Fig. 12, first, in the spatial region, the trajectory of the voyage is divided into n stages along the reference course. For the example in Fig. 12, the straight line between the departure $\mathbf{P}_0$ and the destination $\mathbf{P}_n$ is the reference course, while for practical ship route planning, the reference course is often chosen as the great circle course as in Fig. 8. For each stage i , several waypoints perpendicular to the reference course are pre-defined and denoted by $\mathbf{P}_{i,j}$, $j=1, 2, \dots, m$, providing candidate sailing waypoints for the route planning.

Second, let the expected sailing time be denoted by T . In the temporal region, the sailing time range is discretized into a series of time steps with intervals Δt , i.e., $\Theta = [0, \Delta t, 2\Delta t, 3\Delta t, \dots, T+\Delta T]$, where ΔT is the time delay in addition to the expected sailing time T and can be taken from several hours to days. The time interval set, i.e., $\Delta t = t_{j,k} - t_{j,k-1}$ is chosen as a fixed value, e.g., 30 minutes to 3 hours, depending on the spatial resolution of the waypoints. The sailing time extension will allow for multi-objective and global optimization, e.g., significantly save fuel or reduce damage/ship motions by arriving at the destination several hours late. Then, all waypoints at the i -th stage, $\mathbf{P}_{i,j}$, $j=1, 2, \dots, m$, are associated with the same passing/arrival times $t_{i,k}$ ($k=1,2,\dots$), where $t_{i,k} \in \Theta$ denoted as an initial time set here. In the lower plot of Fig. 12, the vertical dots at each stage represent the initial time set Θ . However, due to a ship's operational constraints, e.g., a ship's heading cannot divergence too much from its destination, a ship's sailing speed is limited by its engine power, etc., not all the times $t_{j,k}$ in the time set can be assigned to a pre-defined waypoint $\mathbf{P}_{i,j}$. Actually, the number of possible passing time points for each stage increases monotonically as the voyage stage advances, i.e., k increases as the stage i . As shown in the lower plot of Fig. 10, the red dots are the accessible time points for different stages and the black dots are those that are eliminated from the initial time set Θ . Therefore, each geometrical waypoint $\mathbf{P}_{i,j}$ is composed of k sailing state $t_{i,k}$, which is denoted by a new symbol $\mathbf{P}_{i,j,k} = \mathbf{P}_{i,j}(t_{j,k}) = [x_{i,j}, y_{i,j}, t_{i,k}]$, ($k=1,2,\dots$).

Third, every sailing state $\mathbf{P}_{ijk}$ from adjacent stages, i.e., the sailing states at the i -th and $i+1$ th stages, are connected to form various paths/edges. To provide a feasible solution and save computation effort, constraints are added to eliminate possible sailing states from further consideration. The constraints are also presented in Fig. 1, in particular, a ship's sailing capability should be considered in the constraints, e.g., not capable to sail in sea conditions with more than 8 metres of significant wave height or not capable of sailing more than 20 knots. The red dashed lines in Fig. 12 are examples of infeasible connections/paths. For the voyage optimization problem, each path is assigned a cost that may be connected and computed by the objective function models. A static 3D weighted path graph system is constructed as shown in Fig. 12.

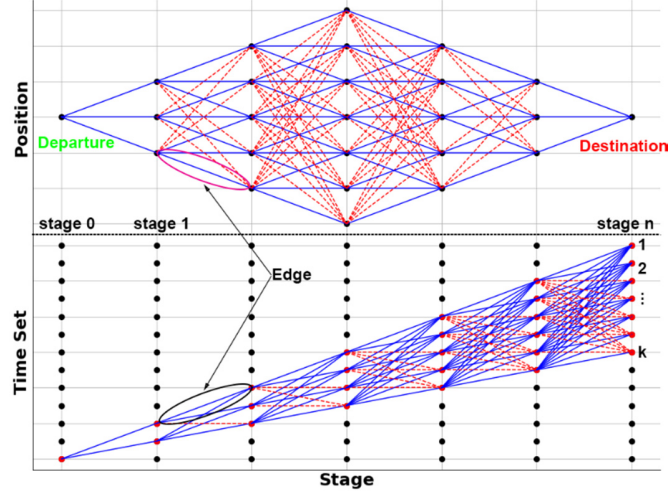


Fig. 12. An example of illustration of 3D graph for route optimization

Finally, the Dijkstra algorithm is used to calculate a preliminary optimal path with minimum objective values for each state of the destination. For this example, the algorithm will generate k end states that correspond to k optimum routes with various ETAs. The k candidate optimum routes generated by the Dijkstra algorithm are denoted by:

$$\overrightarrow{P_{DA}^*} = \begin{bmatrix} \overrightarrow{P_1^*} \\ \overrightarrow{P_2^*} \\ \vdots \\ \overrightarrow{P_k^*} \end{bmatrix} = \begin{bmatrix} P_0 & P_{1,j_{11}}(t_{1,1}) & \cdots & P_{n-1,j_{n-1,1}}(t_{n-1,1}) & P_n(t_{n,1}) \\ P_0 & P_{1,j_{11}}(t_{2,2}) & \cdots & P_{n-1,j_{n-1,2}}(t_{n-1,2}) & P_n(t_{n,2}) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ P_0 & P_{1,j_{11}}(t_{n,k}) & \cdots & P_{n-1,j_{n-1,k}}(t_{n-1,k}) & P_n(t_{n,k}) \end{bmatrix} \quad (16)$$

Theoretically, if provided with a very fine resolution 3D path-graph system, the Dijkstra algorithm is able to obtain a globally optimum ship route plan. However, the computational effort for both constructing the graph and implementing the Dijkstra algorithm will be large. Therefore, this study proposed to implement the Dijkstra algorithm into a low-resolution 3D weighted path-graph system that is then combined with a genetic algorithm to further optimize the ship route optimized by the Dijkstra algorithm. The goal of utilizing the genetic algorithm is to improve the optimal ship routes generated from the Dijkstra algorithm through fine adjustment of $\overrightarrow{P_l^*}$ in terms of location and speed/time. The combination approach of both Dijkstra and Genetic algorithms is termed the hybrid optimization algorithm here, and the scheme of the proposed hybrid algorithm is presented in Fig. 11.

Genetic algorithm

A genetic algorithm is a search heuristic inspired by Charles Darwin's theory of natural evolution (Charles, 1859), which reflects the process of selection in nature, i.e., the best individuals are selected for reproduction of the next generation. Four phases are examined in a genetic algorithm

in this optimization problem. The workflow of using the Genetic algorithm for route optimization is presented in Fig. 11 (right plot).

1. Initial population

The output of the above Dijkstra's algorithm (Dijkstra, 1959) yields a series of optimum routes $\vec{P}_l^*$, $l=1, 2, \dots, k$, corresponding to k different ETAs. For a simple description, let us choose an optimum route denoted by $\vec{P}^*$. The chosen route is composed of a series of waypoints simply denoted by the following description:

$$\vec{P}^* = \begin{bmatrix} P_0(t_0) \\ P_1(t_1) \\ \vdots \\ P_n(t_n) \end{bmatrix} = \begin{bmatrix} x_0 & y_0 & t_0 \\ x_1 & y_1 & t_1 \\ \vdots & \vdots & \vdots \\ x_n & y_n & t_n \end{bmatrix} \quad (17)$$

A new individual will be created by adding some random deviation to the optimum route in Eq. (17). The deviations defined here have two sets of random variables, one for the deviations of the geometrical waypoints along the route, and the other for the deviations of arrival times at each waypoint. The initial population of the deviation is denoted by:

$$\vec{D} = \begin{bmatrix} 0 & 0 & 0 \\ \Delta x_1 & \Delta y_1 & \Delta t_1 \\ \vdots & \vdots & \vdots \\ \Delta x_{n-1} & \Delta y_{n-1} & \Delta t_{n-1} \\ 0 & 0 & 0 \end{bmatrix} \quad (18)$$

where the random variables Δx_i , Δy_i , and Δt_i are assumed to be uniformly distributed among the spatio-temporal resolution of the pre-defined waypoint grid system. By employing a Monte Carlo simulation method, a large number of sample ship routes around the optimum route $\vec{P}^*$ will be generated. These routes are referred as the route population, while each route sample is referred to as an individual in the genetic algorithm. In the following step, the fitness value for each individual ship route should be calculated as a criterion for the selection of breeding in the algorithm.

2. Fitness function

The fitness function is the same function as the objective function, which can be interpreted as the ship performance model from Section 2.1. In the whole generated route population, an individual route sample is generated by adding the set of simulated random vectors $[\Delta x_i, \Delta y_i, \Delta t_i]$ into one of the optimum routes generated by the Dijkstra algorithm as in Eq. (19):

$$\vec{I} = \vec{P}^* + \vec{D} = \begin{bmatrix} \hat{P}_0(t_0) \\ \hat{P}_1(\hat{t}_1) \\ \vdots \\ \hat{P}_n(\hat{t}_n) \end{bmatrix} = \begin{bmatrix} x_0 & y_0 & t_0 \\ x_1 + \Delta x_1 & y_1 + \Delta y_1 & t_1 + \Delta t_1 \\ \vdots & \vdots & \vdots \\ x_{n-1} + \Delta x_{n-1} & y_{n-1} + \Delta y_{n-1} & t_{n-1} + \Delta t_{n-1} \\ x_m & y_{m+1} & t_n \end{bmatrix} \quad (19)$$

The fitness values of all individual sample routes composed of a series of sub-paths are calculated by the fitness function (here for one individual sample route):

$$f_{sample} = \sum_{i=0}^n f(\mathbf{U}(\hat{\mathbf{P}}_i), \mathbf{W}(\hat{\mathbf{P}}_i)) \Delta\tau_i \quad (20)$$

where $\mathbf{U}$ and $\mathbf{W}$ are the ship's operational parameters (speed, heading angle), and MetOcean conditions encountered, and $\Delta\tau_i$ is the time interval between adjacent stages/states in the optimized ship route obtained from the Dijkstra algorithm, i.e., $\Delta\tau_i = \hat{t}_{i+1} - \hat{t}_i$.

3. Selection for breeding

The selection of the “parent” candidate routes for the breeding of next generation uses the stochastic universal sampling method introduced by Baker (1986). It is a development of the fitness proportional selection method. In this case, all the routes generated from the previous steps are used as the route population; a certain percentage of the population, e.g., 20% used here, will be selected as samples for the next generation of breeding. The relative probability of choosing an individual route from the population is equal to the inverse function of the fitness of the route as in Eq. (20). In addition to those 20% selected individuals, another 80% of the new population are generated from the 20% of selected routes as “parents” routes. The generation is by means of the following crossover and transfusion approach.

4. Crossover and transfusion

First, randomly choose a stage, denoted as the m -stage, in the discretized path graph system. All of the above-chosen 20% parent routes are separated at the chosen stage. Then, randomly choose two parent routes for the crossover operation, and let $\overrightarrow{\mathbf{D}}_1$ and $\overrightarrow{\mathbf{D}}_2$ represent the deviation sample in the parent route as shown in Eq. (21):

$$\overrightarrow{\mathbf{I}}_1 = \begin{bmatrix} 0 & 0 & 0 \\ \Delta x_{1,1} & \Delta y_{1,1} & \Delta t_{1,1} \\ \vdots & \vdots & \vdots \\ \Delta x_{m,1} & \Delta y_{m,1} & \Delta t_{m,1} \\ \vdots & \vdots & \vdots \\ \Delta x_{n-1,1} & \Delta y_{n-1,1} & \Delta t_{n-1,1} \\ 0 & 0 & 0 \end{bmatrix}, \overrightarrow{\mathbf{I}}_2 = \begin{bmatrix} 0 & 0 & 0 \\ \Delta x_{1,2} & \Delta y_{1,2} & \Delta t_{1,2} \\ \vdots & \vdots & \vdots \\ \Delta x_{m,2} & \Delta y_{m,2} & \Delta t_{m,2} \\ \vdots & \vdots & \vdots \\ \Delta x_{n-1,2} & \Delta y_{n-1,2} & \Delta t_{n-1,2} \\ 0 & 0 & 0 \end{bmatrix} \quad (21)$$

After separation of the two deviation samples from the parent routes, the new deviations of the crossover with respect to geometrical and arrival-time differences are written as in Eq. (22):

$$\overrightarrow{\mathbf{I}}_{New} = \begin{bmatrix} 0 & 0 & 0 \\ \Delta x_{1,1} & \Delta y_{1,1} & \Delta t_{1,1} \\ \vdots & \vdots & \vdots \\ \Delta x_{m-1,1} & \Delta y_{m-1,1} & \Delta t_{m-1,1} \\ \Delta x_{m,2} & \Delta y_{m,2} & \Delta t_{m,2} \\ \Delta x_{m+1,2} & \Delta y_{m+1,2} & \Delta t_{m+1,2} \\ \vdots & \vdots & \vdots \\ \Delta x_{n-1,2} & \Delta y_{n-1,2} & \Delta t_{n-1,2} \\ 0 & 0 & 0 \end{bmatrix} \quad (22)$$

Transfusion is achieved by adding the new deviation individuals into the input optimum/reference route, here referring to $\vec{P}^*$ in Eq. (17). Repeat this process until the size of the new population reaches that of the old one; then a new optimum ship route can be found according to the fitness values.

An example for illustrating the functionality of the genetic algorithm in the hybrid routing optimization algorithm is shown in Fig. 13. The genetic algorithm used here makes very small adjustments for both the position and time. These small adjustments can perfectly solve the resolution problem mentioned previously. It should be noted that the improvement by the genetic algorithm is small because the 3D weighted path-graph system is already very high resolution from the Dijkstra algorithm.

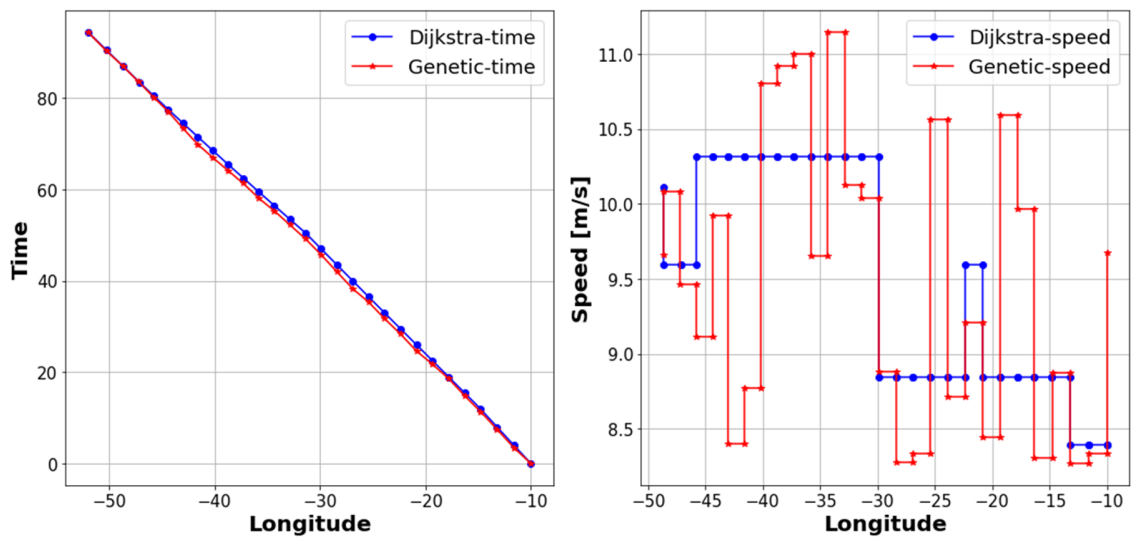


Fig. 13. Adjustment for time and speed by genetic algorithm

2.4. Assumptions and limitations

The drawbacks and limitations of different voyage optimization algorithms have been discussed above. The general assumptions and limitations are listed here:

- It is assumed during the process of the optimization simulation that the weather forecast data are 100% correct. The decisions for route planning for long voyages depend mainly on the weather forecast.
- The uncertainties for voyage optimization algorithms caused by parameter settings are not clear. Different parameter settings have diverse results of the routing optimization.
- It is assumed that objective functions incorporating different ship performance models are almost correct. The accuracy of the models influences the quality of the objective function f . As a consequence, the accuracy of the optimization results is influenced as well.
- Optimization algorithms that discretize the voyage into stages assume that the weather within a certain time interval does not change much. Most of the voyage optimization algorithms discretize the voyage in different forms. The instantaneous cost function calculates the cost of a certain point at a certain time. Too much change in weather during a short interval will lead to a wrong calculation for the route planning.
- Optimization algorithms that discretize the voyage into stages balance refinement of the grid system with computational time. Higher resolution for grid systems can result in more accurate optimization results.
- It is extremely difficult to find a global optimal solution for a voyage because the solution has a high dependence on weather data, which cannot be formulated.

3 Results

This chapter provides an overview and brief summary of the most important results presented and discussed in the three appended papers.

3.1. Summary of Paper I

Various voyage optimization algorithms have been implemented in the maritime domain for optimum planning. Paper I benchmarks five commonly used algorithms to investigate their capabilities for optimum-route planning with respect to expected time of arrival, minimum fuel cost and storm avoidance. The advantages and disadvantages of these algorithms, i.e., Isochrone, Isopone, Dynamic programming, 3D Dynamic programming and Dijkstra's algorithm, are compared as well.

In the paper, a modified Isochrone algorithm is implemented by dividing a ship's voyage into several sailing stages. At each stage, a ship is assumed to sail at an equivalent time. A stage begins by varying the ship's heading angles at each interim waypoint around the reference route, the great circle path between the departure and destination. The range and resolution of heading variations for each waypoint determine the number of potential ship sub-routes. Second, the Isopone algorithm is coded to plan a ship's route by discretizing a voyage into several stages of equal fuel consumption. This method determines the waypoint of the next stage with minimum fuel by tracing back the headings and speeds. This means that each state in the Isopone method is extended to three dimensions by adding the time to the geographical sailing area. Third, by constructing a pre-defined waypoint/grid system based on the great circle reference path along the sailing area as in Fig. 14, a Dynamic programming algorithm is implemented to search for a local optimum ship sub-route with minimum fuel cost.

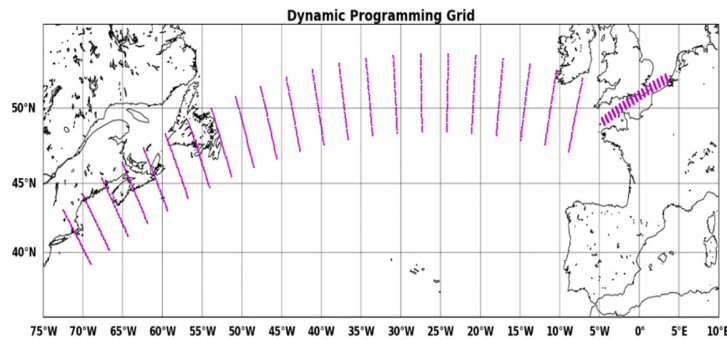


Fig. 14. Grid system used in the dynamic programming method

The input to the dynamic programming is that we assume the ship will sail at a fixed speed for the entire voyage. Under this input constraint, all sub-routes with a local optimum solution will form a global optimum ship route. Furthermore, this paper refined the resolution of the grid system as in Fig. 14. Then, the Dijkstra algorithm for the same path-searching strategy as in Dynamic programming was applied to find the optimum ship route for the specific voyage. However, to allow for speed variations along a ship's voyage, a 3D Dynamic Programming method was implemented by adding time variations to each waypoint. The method uses the voyage progress as stage variable through voluntary or involuntary speed/power control; every stage is composed of

many states, each state defined by a location and discretized time series. In this case, by setting the criterion of choosing candidate waypoints as the local optimum sub-path, e.g., minimum fuel cost, the formation of all local optimum sub-paths cannot be treated as a global optimum route.

A chemical tanker to be sailing in the North Atlantic was chosen as an example to benchmark these optimization algorithms. Two planning strategies were used for the optimization process, i.e., input parameters, as either fixed power or fixed speed along the ship's voyage. In the fixed-speed-based study, the ship keeps a constant speed during the voyage. However, when the marine engine power required at a certain sailing speed exceeds the ship's engine capability, the speed will be involuntarily reduced. In the constant-power-based study, the ship keeps constant power during the voyage and its speed changes due to different weather and sea conditions.

The sailing time and fuel consumption estimated by different optimization algorithms are presented in Table 2. In fixed-speed based planning, the sailing time and fuel consumption estimated by the isopone method, dynamic programming method and Dijkstra's algorithm were close to each other. The result given by the isochrone method has a longer sailing time because the node selection criterion was set to lowest cost. The ship travels, however, a longer distance than using other methods. In the fixed-power based case study, the results of sailing time and fuel consumption estimated by all methods except the 3D dynamic programming are quite similar to each other. In this case study, the waypoint selection criterion was set to be the longest distance from departure. The waypoint selection criterion has a great influence for the results optimized by the isochrone method. The 3D dynamic programming yields a longer sailing time and lower fuel consumption because of the speed variations and the voluntary speed reductions during the voyage. The results given by the fixed-power based study gives a smaller estimated sailing time but higher fuel consumption than those given by the fixed-speed based study. This is because the speed in the fixed-power based study is generally higher than the speed in the fixed-speed based study.

Table.2. Sailing time estimated by different optimization algorithms.

Planning strategy	Isochrone		Isopone		2DDP		3DDP		Dijkstra	
	Time(hour)	Fuel (ton)	Time(hour)	Fuel (ton)	Time(hour)	Fuel (ton)	Time(hour)	Fuel (ton)	Time(hour)	Fuel (ton)
Fixed speed based	171.8	732.4	166.4	695.6	166.2	695.6	173.4	638.0	166.4	692.7
Fixed power based	165.6	702.1	166.0	702.7	165.7	700.3	173.4	638.0	165.6	700.1

Fig. 15 shows that 3D dynamic programming method yields quite different speed variations because the speed and power used varied simultaneously. It had more capabilities (voluntary speed reduction during harsh weather conditions) and better results (saving approximately 8% of fuel) for voyage planning. However, Fig. 15 also shows that these optimization algorithms were not able to avoid harsh weather during the voyage. The 3D dynamic programming method was able to reduce speed when encountering a storm. However, the result shows that it still encountered the largest wave of all the methods. This may be because the storm was moving towards the departure point, and reducing speed could not help to avoid the storm.

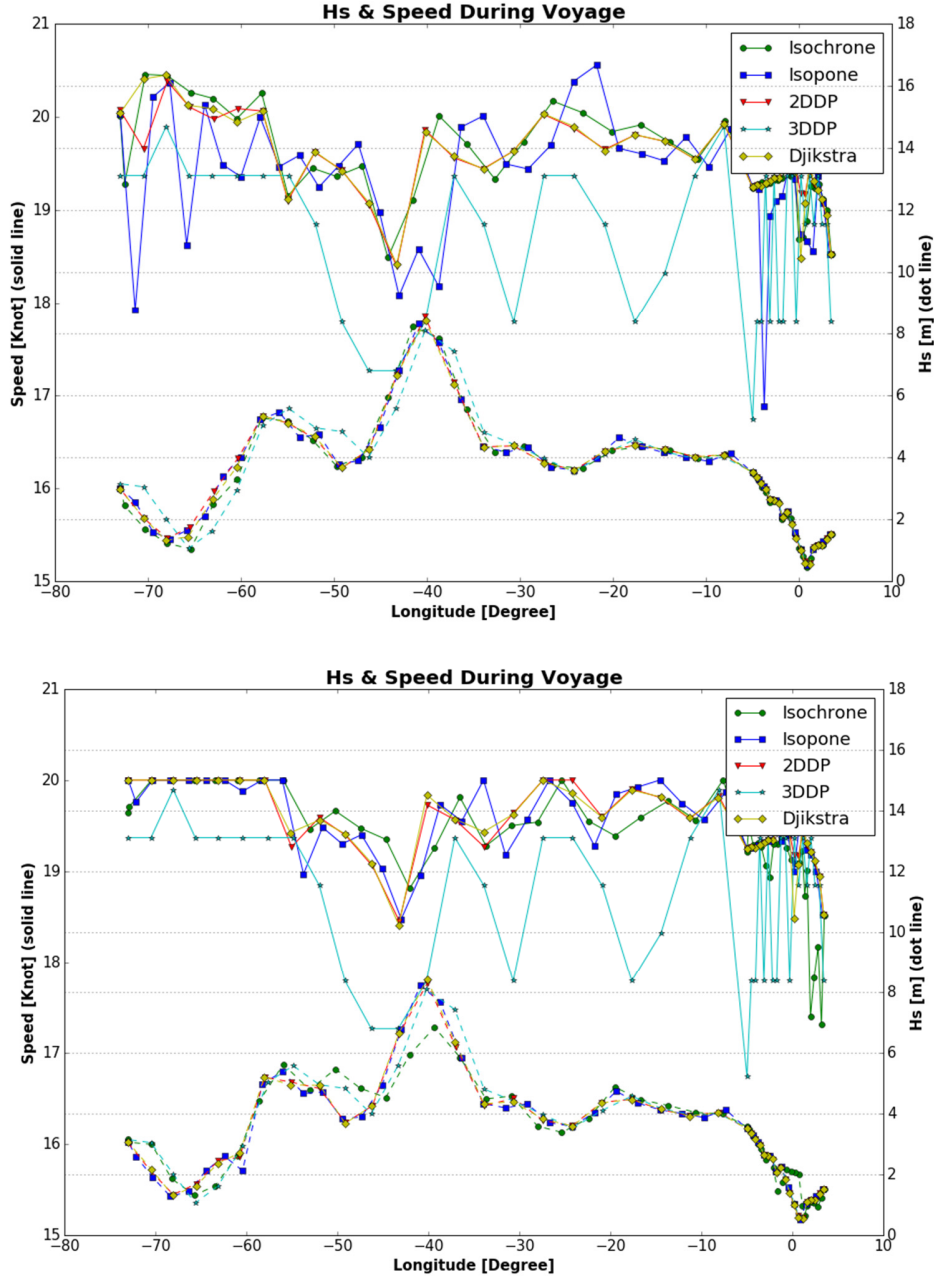


Fig. 15. The ship speeds achieved during the optimized ship courses (shown as solid lines) and the wave conditions encountered (significant wave heights H_s shown as dashed lines) for fixed-speed-based and fixed-power-based studies.

3.2. Summary of Paper II

In this paper, the voyage optimization algorithms introduced in Paper I are further categorized into two groups, dynamic-grid-based methods and static-grid-based methods. To study the benefits of voyage optimization systems on the reduction of fatigue crack propagation in ship structures, i.e., potential extension of sailing life before crack repairs are required, both voyage optimization methods were combined with a linear elastic fracture mechanics model as in Mao (2014), which

could predict the crack propagation speed in ships in terms of the MetOcean and sailing conditions encountered. In this paper, a 2800TEU container ship sailing in the North Atlantic with an initial crack length assumed to be 100 mm was assumed for the demonstration analysis. Full-scale measurements of the ship's navigation during 2008 were available for this case study.

This study compares the crack propagations if the vessel were sailing along four planned ship routes, i.e., the great circle, routes calculated by the Isochrone and dynamic programming methods, and the measured original sailing routes. All ship routes were expected to reach the destination at approximately the same time (ETA as measured). The crack propagation results for these sailing routes are plotted in Fig. 16. The graphs demonstrate a great reduction of crack propagation when using optimization algorithms in comparison with the conventional great circle sailing routes. The great circle routes are the shortest paths for these voyages, but the fatigue crack propagated along these routes much farther than was calculated for other routes. It should be noted that the original routes were also obtained from an old-fashioned weather routing system. In general, the benefit of the reduction of fatigue crack propagation in ship structures or sailing life extension is quite significant, i.e., with a maximum life extension of 100% in this case study.

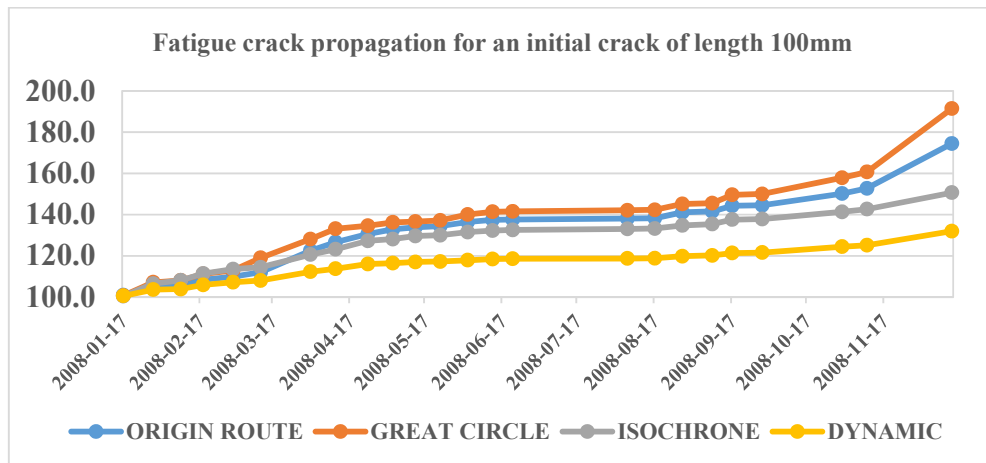


Fig. 16. Fatigue crack propagation for an initial crack of length 100mm during 2008

This paper additionally calculates the voyage optimization of both eastbound and westbound voyages to compare the benefits of sailing in different directions. The voyage optimizations of two typical routes, i.e., one eastbound and one westbound, are shown in Figs. 17 and 18, respectively. For the eastbound voyage in Fig. 17, the ship sailing along its actual route encountered the worst sea conditions. The routes optimized by the dynamic programming and isochrone methods are longer than the actual route, but the crack propagation is lower due to encountering more calm sea conditions. Fig. 18 shows that if the ship sails along the route optimized by dynamic programming, it will encounter the calmest sea conditions. This explains why route planning with dynamic programming can result in minimum crack propagation along the voyage. In general, the benefits of using a voyage optimization algorithm are not obvious for eastbound voyages in the North Atlantic, in particular during summer seasons. In some winter voyages, crack propagation can be reduced by more than 50% if sailing along routes recommended by these optimization algorithms. This is because in the North Atlantic, storms with severe MetOcean conditions always move from west to east and provide much potential for route planning to avoid these storms.

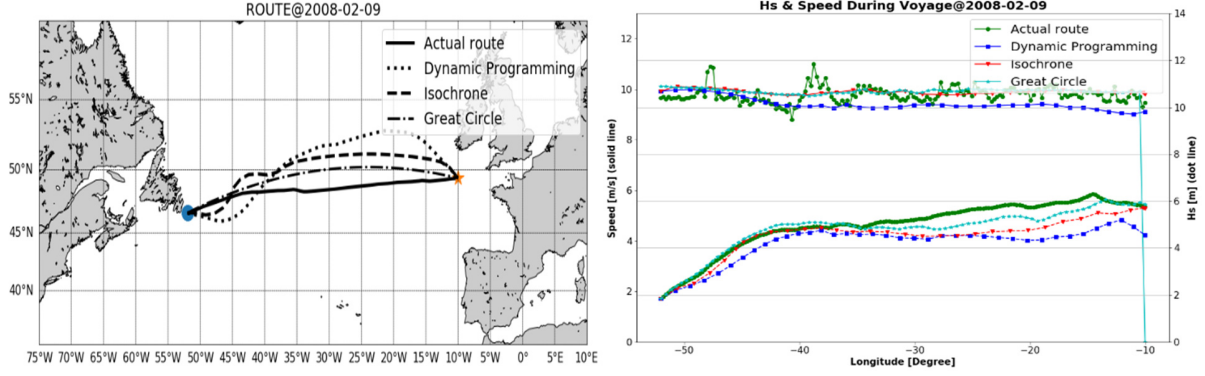


Fig. 17. Typical voyage-planning results for the eastbound Voyage 2008-02-09

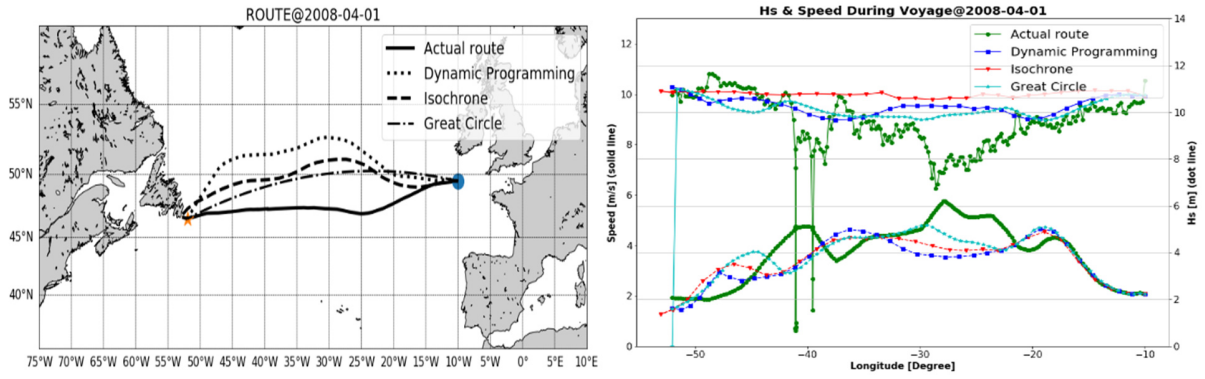


Fig. 18. Typical voyage-planning results for the westbound Voyage 2008-04-01

3.3. Summary of Paper III

The conventional voyage optimization algorithms studied in Paper I are unable to provide globally optimal routes for ships if one allows for speed/power variations along the voyage. Therefore, this paper attempts to develop an algorithm that allows for both global optimization capability and computational efficiency. A hybrid routing-optimization algorithm (HROA) is proposed to provide at least the following improvements: 1) provide globally optimal routes for ships; 2) solve multi-objective optimization problems for route planning.

The scheme of the HROA is shown in Fig. 19. Before implementing Dijkstra's algorithm and the genetic algorithm, a 3D graph/grid system should be generated whose nodes/waypoints are created with the information of geometric points in the voyage and the time set. The edges/paths are to be generated by the nodes/waypoints, considering the constraints during the voyage. The edges/paths are assigned with weights based on weather information and the ship performance model. Dijkstra's algorithm is used with the 3D graph/grid system to find candidate optimum routes with a series of ETAs. Those candidate routes will be refined by a genetic algorithm. Finally, the genetic algorithm will provide an optimal route extremely close to the globally optimal route for route planning. To demonstrate the benefit of using the hybrid routing-optimization algorithm, an actual ship route sailing the North Atlantic (Mao et al., 2010) was compared with the optimized route

given by the hybrid routing optimization algorithm. Comparisons with other conventional voyage optimization algorithms, i.e., the Isochrone method and the dynamic programming method, were conducted as well.

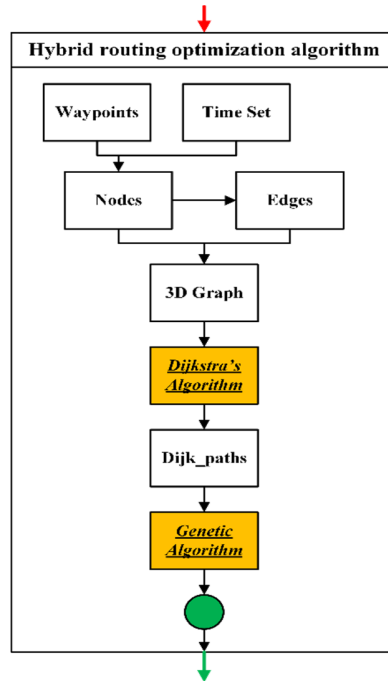


Fig. 19. Scheme of the hybrid model for ship route optimization

In the case study, the actual voyage began on 2008-01-17 and ended on 2008-01-26. Sixty-five optimized candidate routes were generated as shown in Fig. 20. The estimated times of arrival ranged from 96 to 128 hours with 0.5 hour time intervals. They form a bi-objective curve with respect to power consumption and ETA as shown in Fig. 21. The plot presents the estimated total engine power consumed for all of the sixty-five optimized candidate routes in terms of various ETAs, while the red dots present the bi-objective optimization Pareto Front of the route optimization results.

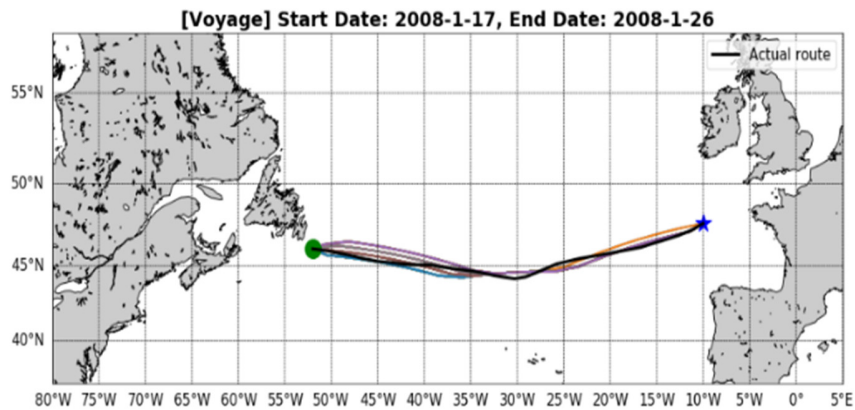


Fig. 20. Sixty-five generated candidate routes with different ETAs

Fig. 21 additionally indicates that the optimum route for this voyage should have an ETA between 105 h and 110 h. The routes with longer ETAs shown in blue dots indicate inefficient routes with the respect to both power consumption and time cost. This plot can help users make trade-offs for power consumption and ETA. Fig. 22 presents three candidate trajectories calculated by HROA, the isochrone method and the dynamic programming method. From its onset, the optimized route found by HROA is different from those of the other methods. This is because HROA attempts to provide a globally optimal route, which can be explained by Fig. 23. Fig. 23 compares the significant wave heights H_s and sailing speeds along the actual route, optimal routes obtained by conventional methods, and HROA. At the very beginning of the voyage, the HROA tried to lower the speed. As the consequence, HROA successfully avoided the most severe sea conditions in the middle of the voyage, while the results of conventional methods encountered the largest waves.

The hybrid routing-optimization algorithm can optimize a ship route with the respect to multiple objectives such as fuel consumption and ETA. It can also yield a globally optimal route that avoids multiple storms during a voyage.

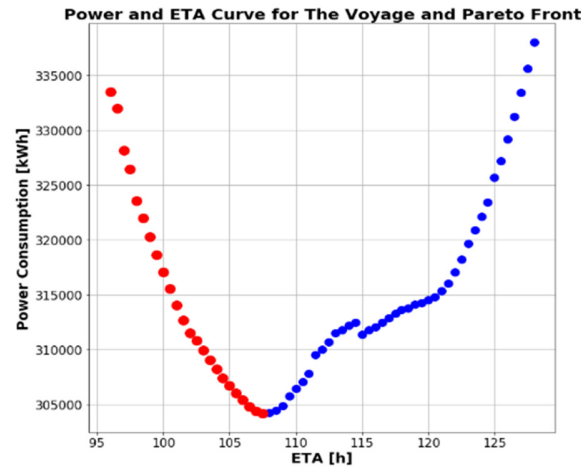


Fig. 21. Pareto Front for power and ETA of the voyage

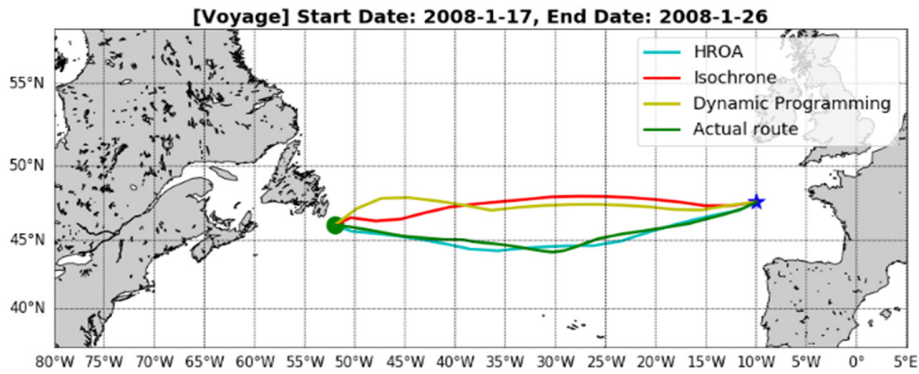


Fig. 22. Optimized routes compared to actual route

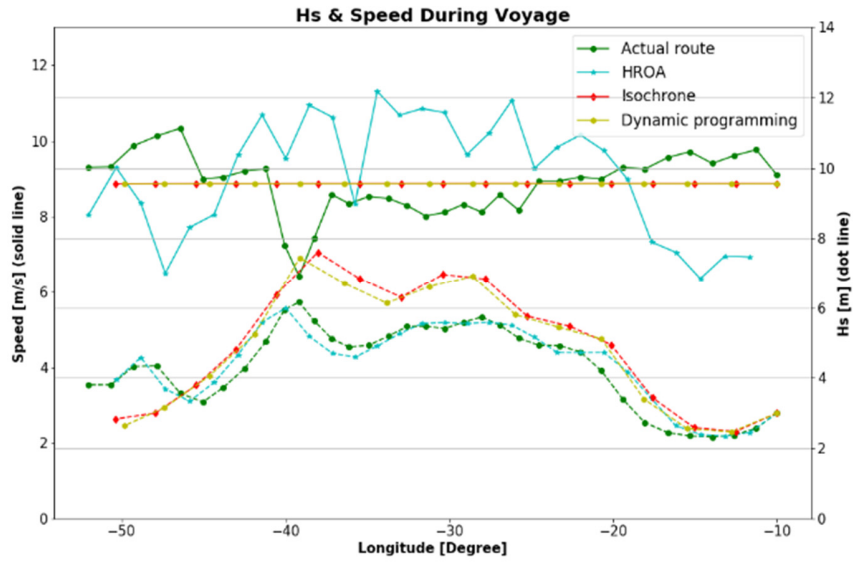


Fig. 23. Significant wave heights H_s encountered and ship speed profiles compared between actual measurements and our optimized routes

4 Conclusions

This thesis first carried out a benchmark study of five conventional voyage optimization algorithms to compare their advantages and disadvantages for optimizing ship routes. It is found that the Dijkstra's algorithm and the Dynamic programming algorithm can find the best route from a pre-defined waypoint/grid system. However, the accuracy of the solution is highly dependent on the grid resolution, which is directly linked with the required computational effort. The advantage of using a predefined grid system is that it can easily handle impassable areas. The Isochrone and Isopone methods are more suitable for single objective optimization, while the 3D dynamic programming algorithm is more capable of analyzing dynamic weather, essential for both voluntary and involuntary speed reduction.

The impact of using voyage optimization to address fuel consumption and crack propagation was investigated as well. The results demonstrate that the optimized routes generated by those algorithms differ significantly from a great circle because of storms along the route. The algorithms can help the ship to avoid severe storm conditions, leading to diminished fatigue-crack propagation and enhanced ship structural integrity. In particular, the dynamic programming method can help to increase vessel service time by 50%. It should be noted that the algorithms used in this study are not capable for providing globally optimum routes. A global-optimization algorithm is expected to yield a more optimized solution for a voyage plan.

To overcome the disadvantages of conventional voyage optimization algorithms and allow for multi-objective route optimization and permit speed/power variations during a ship's voyage, a hybrid routing-optimization algorithm is proposed in this study. It provides a solution route plan extremely close to the globally optimal solution. With respect to reducing power consumption during a voyage that may encounter several severe sea conditions, it was found that this algorithm can give a solution with minimum fuel cost. The results obtained from the case study demonstrate that the hybrid optimization algorithm can provide ship routes that fulfil multi-objectives, such as accurate ETA and minimum fuel consumption. The hybrid routing-optimization algorithm has substantial potential to lower the cost and reduce the risk of, e.g., fatigue damage accumulation or crack propagation in ship structures. It can plan a ship's sailing route with an accurate expected time of arrival. The case study demonstrated that the hybrid optimization algorithm can easily avoid high H_s in a storm zone. In addition, it was demonstrated to be a suitable method for providing reliable routes for sailing in rough sea conditions, such as the North Atlantic sailing. It can additionally give the Pareto route Front, which provides an optimum ship route with respect to, e.g., minimum fuel cost, as a function of time. This Pareto Front can give more background information to ship operators with more choices of ETAs.

5 Future work

There are two main areas of focus for future research work: further development of the initially proposed hybrid optimization algorithm and study of its sensitivity for various optimization objectives and application of machine-learning algorithms to real-time updates of a ship's performance models used in the optimization, e.g., the speed-power relationship and motion-to-wave model, process.

More specifically, the first area is power-variation-based routing optimization and its integration into the hybrid optimization algorithm. Current voyage optimization algorithms use either fixed speed/power or vary speed along the voyage as inputs for the voyage optimization. However, for actual ship operation at sea, captains navigate a ship by adjusting its engine power or engine RPM to speed up or slow down. It will be difficult to advise that a ship sail with pre-defined/planned speeds along the voyage. Thus, it would be beneficial to develop an optimization algorithm that uses the ship's engine power/RPM as inputs in different stages during the voyage. The development of such an algorithm requires a highly accurate reverse ship speed-to-power model. Additionally, it will require at least three times more computational effort than a speed-to-power model. Thus, a more advanced method should be developed for a power-based voyage optimization.

As noted in the benchmark study of Paper I, the final solution of an optimized ship route will depend strongly on the parameter settings used in the voyage optimization algorithm, such as the resolution of the waypoint/grid system and the criteria for choosing candidate routes for optimum sub-routes. For example, Fig. 25 presents optimum routes generated by the isochrone method by setting different parameters, i.e., grid resolution and changing criteria of choosing the best waypoints at each stage. The generated optimum routes are significantly diverse, implying the need for sensitivity analysis of various optimization algorithms. In this study, sensitivity analysis, varying individual input parameters, will be used to describe how uncertain a final optimum route is with respect to various objectives. Sensitivity analysis will be additionally regarded as a prerequisite in the assessment of computational engineering models.

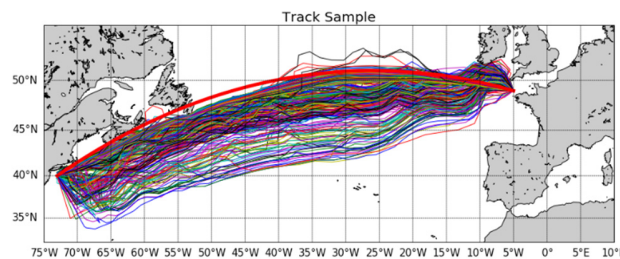


Fig. 24. Sample routes for different parameter settings

Finally, a ship's performance models are key elements affecting the voyage optimization results. In the present study, the ship power/fuel consumption models include semi-empirical models, theoretical models, and basic statistical models to fit the residual between the measured and predicted performances by theoretical models. These approaches provide a good estimate of power/fuel consumption, but they are not accurate enough. Therefore, the other area for my future work is to combine theoretical modelling with machine learning algorithms to update a ship's performance models in real time.

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