WHITE PAPER

Balancing transit time, fuel costs and environmental impact to map out the shipping route

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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. This white paper starts with an introduction to familiarize readers with the voyage optimization system and what it entails. It then gives an emphasis on the comparison of conventional approaches with the evolution approaches. Finally, it proposes usage of hybrid approach over conventional approaches to derive maximum business value.

1. Introduction and Methodology

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. In addition, The rapid increase and fluctuations of the fuel price and social awareness of air emissions from the ships has also given rise to a need to plan for optimum waypoints and speed for ocean voyages with minimum fuel consumption, keeping the expected time of arrival and ship's safety constraints into consideration for the route planning. Among all available energy efficient solutions, A sail plan system having the concepts of weather routing and voyage optimization combined can prove to be the most cost-effective and efficient measure to ensure a ship's safety, gain more economic benefit, and reduce negative effects on our environment.

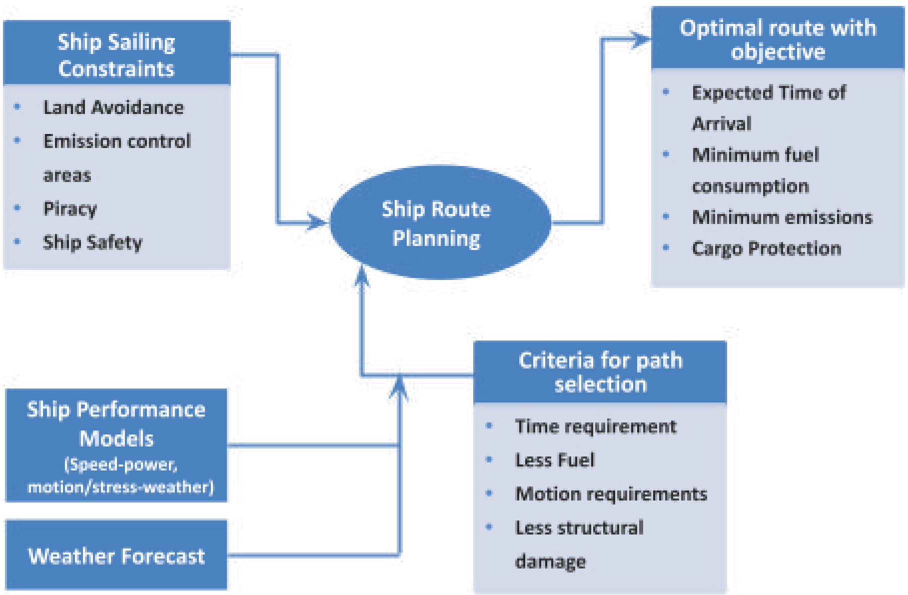

Figure 1: Ship Route Planning Concept

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.

2. Choosing the right pre-planned strategy

In the shipping market various optimization algorithms are available to provide route planning services. However, there are a few points that should be taken into consideration while choosing for the right plan of action as:-

- These algorithms often contain large uncertainties, leading to a large scatter of the recommended optimal route solutions.
- 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.
- Different voyage optimization algorithms may provide different optimization results. Even for the same algorithm, different parameter settings can give diverse optimization results.
- Most of the algorithms focus on single-objective optimization.

Therefore, it's important to study the uncertainties and sensitivities of various conventional routing optimization algorithms, analyze the benefits of these algorithms for various voyage optimization objectives, such as the expected time of arrival, minimum fuel cost and low crack propagation in ships, etc and choose the more sophisticated voyage optimization algorithm to provide a globally optimal ship route plan to guide actual ship operation

3. Conventional Routing Algorithms

The conventional routing optimization algorithms can be categorized into two types, dynamic grid based methods and static grid based methods.

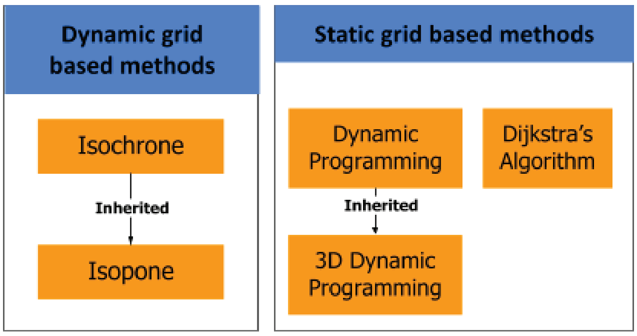

Figure 2: Conventional Algorithms

Dynamic-grid-based methods, which include the Isochrone and Isopone methods, generate nodes in every optimization iteration with the criterion to choose waypoints for each sub-sector be it shortest distance from destination or lowest cost.

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 around a ship's sailing region.

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.

4. Hybrid Route Planning Approach

To allow for multi-objective voyage optimization that can exploit voluntary changes to a ship's speed/power inputs along various sailing stages in the optimization process, a hybrid routing optimization algorithm should be used. This hybrid approach is proposed to consider three-dimensional ship navigation/operation parameters control, i.e., varying ship speed and waypoints so as to perform globally optimized route planning.

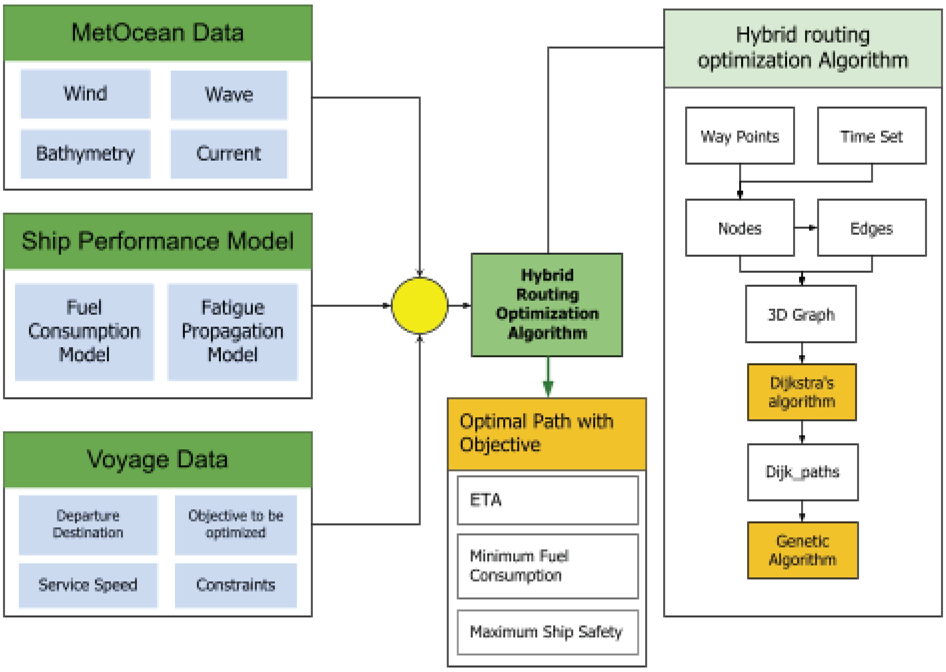

Figure 3: Overall structure of Hybrid Route Planning System

The optimization process contains four basic components/models:

- MetOcean data describes the sea conditions that the ship will encounter
- The ship model predicts a ship's energy performance
- Voyage data captures information from the users, such as objectives that need to be optimized and service speed
- Finally, the route planning algorithm is used to generate an optimum routing schedule with all waypoints and associated passing times

4.1. MetOcean Data

The weather forecasts of MetOcean conditions are used to plan the sailing schedules based on a 7-14 day weather forecast. However, for forecasts longer than 3 days the data contain large uncertainties and most often do not directly include the parameters needed for routing and may only include pressure distributions in the atmosphere. That's why the weather forecasts within a 2-5 days' time span are often sound enough for the route planning. In addition to the MetOcean forecast information, for optimum route planning with different objectives, we must adopt at least three objectives: Expected Time of Arrival (ETA), minimum fuel cost and lowest fatigue-crack propagation. To achieve these objectives, the planning 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.

4.2. Ship Performance Model

Ship performance models describe a ship's performance, e.g. sailing speed, motion/damage response, and fuel cost, in terms of its loading conditions, encountered weather conditions, and operational conditions. These models are the core elements in the route planning process to estimate the cost function for specific objectives.

4.2.1. Ship Fuel Consumption Model

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. In this, an estimation procedure is used to predict the fuel consumption rate using input parameters of encountered weather information, the ship's characteristics, and operational profiles etc. To describe a ship's speed-power relationship, the most important component is to accurately estimate a ship's resistance in different conditions. 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 eventually determines the choice of ship route by the routing optimization algorithm chosen. Since weather and sea conditions are the main factors in weather routing problems an accurate model for estimating the added resistance due to waves is thus an important input for a weather routing system.

4.2.2. Fatigue Crack Propagation Model

The fatigue crack propagation model is then used to predict the crack propagation rate in the ship structures using the above information. 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 for any arbitrary sea state characterized by significant wave height, wave period, and wave spectrum.

4.3. Voyage Data

Hybrid Route Planning System takes into account all meteorological and oceanographic conditions (wind, wave, and current) that a vessel/cargo is expected to experience along a route to predict the weather. In addition, data related to structural characteristics of ships, wind and wave resistance when captured through sensors in real time along with engine power, ship speed, turbine speed data when collected at frequent intervals proves to be an asset for the ship performance model, signifying speed-power relationship. This enables the engine to work on its best operational efficiency in order to adapt with continuously changing external conditions. Moreover, various ship sailing constraints like safety, schedule, cost of operation, fuel consumption, local traffic patterns, no emission areas, etc. from past voyages are taken into account to stump up the route planning approach.

4.4. Hybrid Routing Optimisation Algorithm

For ship route optimization using Dijkstra algorithm, a voyage is first discretized into various stages to construct a waypoint grid/path-graph system using a combination of set of pre-defined waypoints/nodes, and a set of sailing paths/edges composed of pairs of waypoints/nodes 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. The algorithm is based on two principles, i.e. a sub-route within a shortest route is also a shortest subroute and for a given shortest distance between two points A and C, a path going from point A to C through a third point B will always be a distance greater than the direct distance from A to C.

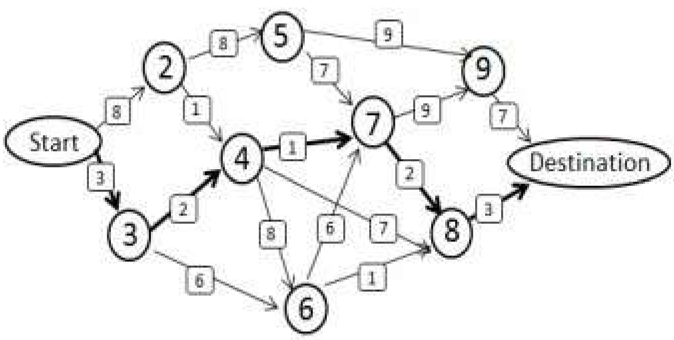

Figure 4: Illustration of the Dijkstra algorithm

The basic concept of this algorithm is presented in figure 4. There are many potential routes sailing from the "Start" point to the "Destination" point. This algorithm first divides a whole route/path into a series of sub-routes. Then the starting point of a sub-route is connected to all of its neighbouring points by paths, which are associated with some cost values like sailing distance, fuel consumption or a weighted combination relative to certain \objective functions. The optimum subroute follows the path with the lowest cost value.

This path and its associated cost value is then taken as reference and used for the following tests. Once a point is reached and its corresponding paths are tested, the current reference cost value is then compared with the preceding subpaths. If the newly tested route turns out to be smaller than the reference, the new cost value and associate path is assigned to that point. Consequently, the previous reference path is dismissed and the new path is taken as reference. Following this procedure, paths evolve towards the destination point. During the whole process, only one optimum route remains. As an example of such a route optimization, the bold lines in the figure 4 mark the optimum route with the smallest value/distance from the "Start" point to the "Destination" point. The predefined grid system generated using this algorithm can easily handle impassable areas, finding the shortest route around or between e.g. islands and no-go zones. In particular, this method is very well suited for route planning.

Additional advantage is achieved when this algorithm is used in combination with the genetic algorithm which helps further optimize the ship route optimized by the Dijkstra algorithm. The output of the Dijkstra's algorithm which consists of a series of waypoints is taken as base and a new route is created by adding some random deviation to the optimum route. The deviations can 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.

By employing Monte Carlo simulation method, a large number of sample ship routes around the optimum route is generated. These simulated routes are referred to 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 is calculated as a criterion for the selection of breeding in the algorithm. The fitness values of all individual sample routes consisting of a series of sub-paths are then calculated by using the fitness function. The fitness function is the same function as the objective function, which can be interpreted as the ship performance model. The selection of the "parent" candidate routes for the breeding of the next generation uses the stochastic universal sampling method. All the routes generated from the previous steps are used as the route population; a certain percentage of this population is then selected as samples for the next generation of breeding. The relative probability of choosing an individual route from the population is then equated against the inverse function of the fitness of the route. In addition to these certain percentages of individuals, another set of the new population is generated from the selected routes as "parents" routes and the process repeats itself.

The usage of the genetic algorithm makes very small adjustments for both the position and time. But these small adjustments can perfectly solve the resolution problem faced by the Dijkstra algorithm. The improvement by the genetic algorithm is small because the generated 3D weighted path-graph system from the Dijkstra algorithm is already very high resolution. The combination approach of both Dijkstra and Genetic algorithms is termed the Hybrid Routing Optimization Algorithm here. Higher resolution for the grid system in turn results in more accurate optimization results as it helps compare the significant wave heights and sailing speeds along the optimal and identified routes. Hybrid Routing Optimisation Algorithm contributes the most in this Hybrid sail system by providing a globally optimal route, benefits for which can be leveraged for an efficient Hybrid Route Planning System avoiding the most severe sea conditions, reducing fuel consumption and air emissions, and at the same time considering ship/cargo/crew safety with an expected time of arrival.

5. Conclusion

In summary, using this hybrid route planning system, a static 3D weighted path-graph system composed of waypoints (i.e., represented by longitude, latitude and time) can be very well created or pre-defined. The Dijkstra algorithm can be used to construct an initial candidate optimum route based on the predefined path-graph system and required objectives. The genetic algorithm can be employed to refine the initial route to generate a globally optimum ship route. The goal of utilizing the genetic algorithm is to improve the optimal ship routes generated from the Dijkstra algorithm through fine adjustment of waypoints/nodes in terms of location and speed/time.

This hybrid route planning approach can optimize a ship route with respect to multiple objectives such as fuel consumption, and expected time of arrival. It can also yield a globally optimal route that avoids multiple storms during a voyage, in turn reducing the risk of, e.g., fatigue damage accumulation or crack propagation in ship structures. In nutshell, this approach can prove to be a suitable one for providing reliable routes for sailing in any sea conditions be it rough or smooth.

However, Story doesn’t end here! The captured output of the model can again be leveraged to offer insights that can be used to measure fuel efficiency and implement policies resulting in less fuel waste. The variance between actual and predicted routes, frequency of acceleration and change in speed and direction can be captured to unearth hidden insights and drive consistent and efficient operations. A feedback based mechanism can be institutionalized by tracking variables like how fast the ship is going, how long it runs, how frequently it changes its directions and more to determine the health of engines which can potentially better alert the supervisors to re-route, considering past failures.

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