Comparing Two Optimization Approaches for Ship Weather Routing

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Abstract Weather routing in maritime shipping is related to a shipping company's objective to achieving maximum efficiency, economy and cost competitiveness by optimizing each voyage of a ship. A voyage can be optimized regarding cost, time, safety or a combination of these factors, while considering forecasted meteorological and oceanographic information as well as constraints given by geographic conditions, ship characteristics, emission regulations, safety requirements or time restrictions. A wide variety of mathematical models of the ship weather routing problem as well as different approaches to solve it can be found in the literature and are applied by numerous software systems. This paper presents two approaches to solve the ship weather routing problem, a graph algorithm and an evolutionary approach. Both approaches aim to minimize fuel costs, allowing for route and speed optimization. They are compared based on numerical examples with real-world data.

1 Ship Weather Routing Problem

Voyage planning and optimization represents a widespread measure to improve cost and energy efficiency of maritime shipping. Ship weather routing generally aims to find an optimal route and speed profile for a ship's voyage based on the analysis of metocean weather forecasts. Meteorological institutes commonly use the mathematically concise data format GRIB (General Regularly-distributed Information in Binary form) to store weather data numerically predicted for each node of a grid. The ship weather routing problem is mathematically modeled in various ways [16].

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Formulations not only range from one to multiple objective optimization problems, but also from constrained graph problems to nonlinear optimization problems. In order to solve the optimization problem, different approaches are applied by several commercial systems which now support voyage optimization on vessels, as well as by numerous academic software developments. These vary from calculus of variations [2], dynamic programming [1, 6, 12] or graph algorithms [4, 7, 14] to evolutionary approaches [5, 9, 13]. Superiority of an approach producing satisfactory results with adequate computational effort significantly depends on the degree to which the specific requirements regarding optimization objectives, variables, constraints and implementation are met [16]. For the ship weather routing problem described below, two popular approaches, a graph algorithm and an evolutionary method, are presented, compared and discussed.

Objective Function The objective is either minimum fuel costs, minimum voyage time, or maximum safety, or these objectives are combined giving rise to a multi-objective problem. As cost and energy efficiency are key aspects in maritime shipping, in this study the objective is minimum fuel costs C_{Fuel}.

Variables To allow route and speed optimization, the ship's heading α_G and speed over ground v_G are introduced as control variables. A certain speed requires variable engine power considering different environmental impacts. Speed and weather conditions are assumed to be constant between two waypoints of the ship's route.

Constraints Constraints on the variables are given by the ship itself, by time, safety and geographic restrictions. For simplicity reasons, safety constraints such as critical wave heights or periods are neglected. Geographic constraints primarily refer to land, but can also include traffic separation schemes, icebergs or mines. As a deep sea voyage is assessed, these constraints are not further elaborated. Time restrictions are most likely related to the estimated time of arrival (ETA). A certain arrival time $t_{Arrival}$ is assumed to be obligatory. Referring to constraints due to ship characteristics, the ship's design and propulsion system influence its behavior, speed profile and fuel consumption when facing environmental impacts such as waves or wind. Considered constraints include a maximum speed through water due to a maximum power of the ship's engine and a minimum speed to maintain course control.

2 Optimization Approaches

The ship weather routing problem as described above is a single-objective deterministic and constrained optimization problem. It is approached below using a graph algorithm and a genetic algorithm. Both approaches aim to minimize fuel costs, while varying the ship's heading and speed to allow route and speed optimization.

Graph Algorithm The described ship weather routing problem is discretized in time and space. An according graph is used, which is connected, directed and acyclic [15]. A common deterministic method for solving a discrete single-objective optimization problem related to finding the optimal path in a graph is Dijkstra's algorithm [3], which is applied in ship weather routing [11, 14]. To reduce computational effort the A* algorithm is applied in this study [15]. An optimal path in this case is the path of minimum fuel costs, thus the arc weights are the fuel costs between the two respective nodes. It is aimed to minimize the total estimated costs $F(k)$, which is the sum of the exact fuel costs $G(k)$ according to Sect. 3 from the start to any node k and the heuristic estimated fuel costs $H(k)$ from k to the destination, which are derived equivalently to $G(k)$ but neglecting the predicted weather conditions. The selection criterion is expressed in Eq. (1) with B denoting a set of nodes not considered on the route from start to k [15].

$$F(k) = G(k) + H(k) \leq \min\{G(i) + H(i) \mid i \in B\} \tag{1}$$

Genetic Algorithm Evolutionary methods, mainly genetic algorithms (GA), are becoming increasingly popular as it is more often aimed at decision support by solving a multi-objective optimization problem [5, 13]. The objective is to find the route r^j of minimum fuel costs $C_{Fuel}(r^j)$ from the set of all feasible routes R. A route's fuel costs are the sum of the costs between two neighboring waypoints i and $i+1$ with $r^j = \{x_1^j, x_2^j, \ldots, x_n^j, y_1^j, y_2^j, \ldots, y_n^j, v_1^j, v_2^j, \ldots, v_n^j\}$ being a vector of decision variables describing the waypoints (x_i^j, y_i^j) and the speed profile (v_i^j). To apply the GA in this case, it is made use of the GA from the optimization toolbox of Matlab R2016a, which is integrated in the C++ framework. An initial population $r^{initial}$ is given for each voyage (see Sect. 4). Using the GA default selection, reproduction, crossover and mutation mechanisms further generations are created until a local optimal solution is provided [8].

3 Ship Hydrodynamics and Calculation of Fuel Costs

The optimization aims to minimize fuels costs. These can be derived based on time- and location-dependent meteorological and oceanographic impacts, especially ocean currents, wind and waves, as well as the ship's characteristics, mainly resistance and propulsion system. As the current is neglected in this study, the ship's speed v_S and heading α_S through water are equal to those over ground. The same applies to true wind speed u_T and direction α_T and those relative to the ground.

Ship Resistance The total resistance of a ship R_{total} is composed of its resistance in calm water R_{Calm} and an added resistance influenced by the ship's roughness and appendages as well as environmental impacts [10]. Here, the added resistances due to wind R_{Wind} and waves R_{Wave} are considered, as in Eq. (2). Wind speed u_T and direction α_T as well as wave period T_W, direction μ_0 and height H_S are given in weather forecasts, while ship speed v_S and heading α_S are variables.

$$R_{total} = R_{Calm}(v_S) + R_{Wind}(u_T, \alpha_T, v_S, \alpha_S) + R_{Wave}(T_S, \mu_0, H_S, v_S, \alpha_S) \tag{2}$$

Calm Water Resistance The calm water resistance R_T of a ship can be derived amongst others from model tests or empirical formulae. It can be expressed as a polynomial function of the ship's speed through water v_S, as in Eq. (3).

$$R_{Calm}(v_S) = a_4 v_S^4 - a_3 v_S^3 + a_2 v_S^2 - a_1 v_S + a_0 \tag{3}$$

Added Resistance due to Wind Due to the effect of the true wind speed u_T at an angle α_T, the ship's speed v_S and heading α_S, the ship experiences an apparent wind speed u_A. To estimate the wind resistance R_{Wind} the simplified approach in Eq. (4) is used that depends on the apparent wind along the ship's center line $u_{A,S} = v_S + u_T \cdot \cos(\alpha_T - \alpha_S)$, the ship's frontal projected area above sea level A_F, the density of air ρ_{Air} and a coefficient c_A, which is 0.8–1.0 for cargo ships [10]. Accordingly, head wind causes an additional resistance, while tailwind reduces the ship's resistance.

$$R_{Wind}(u_T, \alpha_T, v_S, \alpha_S) = \begin{cases} \ 0.5 \cdot \rho_{Air} \cdot c_A \cdot A_F \cdot u_{A,S}^2 & , \quad u_{A,S} \geq 0 \\ -\ 0.5 \cdot \rho_{Air} \cdot c_A \cdot A_F \cdot u_{A,S}^2 & , \quad u_{A,S} < 0 \end{cases} \tag{4}$$

Added Resistance due to Waves The added resistance R_{Wave} can be derived from hydrodynamic calculations. It depends on wave period T_w, encounter angle between ship and wave μ_e, wave height H_S and ship speed v_S. The encounter angle μ_e is the angle between main wave direction μ_0 and ship's heading α_S. Here, the added resistance $R_{Wave,H}$ standardized with the square of the wave height H_S is given in a matrix used to interpolate the added resistance due to waves $R_{Wave}(T_S, \mu_0, H_S, v_S, \alpha_S)$.

Engine Power and Fuel Consumption Accounting for the ship's propulsion system, the ship's resistance results in a required engine power, the fuel consumption and finally the costs of the route. Total resistance R_{total}, ship speed v_S and propulsion efficiency η_D compose the delivered shaft power with a corresponding specific fuel consumption $b_{e,Fuel}$. Combined with voyage time t and price per ton of heavy fuel oil P_{Fuel} it leads to the fuel costs C_{Fuel} as per Eq. (5), which are the time- and space-dependent arc weights of the graph. Losses in shaft or bearings are neglected.

$$C_{Fuel} = \frac{R_{total} \cdot v_S}{\eta_D} \cdot b_{e,Fuel} \cdot t \cdot P_{Fuel} \tag{5}$$

4 Comparison of Results, Discussion and Conclusions

The two approaches are compared based on transatlantic voyages of a bulk carrier transporting coal from Venezuela to Europe using weather forecasts from 2013-12-16. The ship has a length between perpendiculars of 220 m, a breadth of 32.24 m, a draught of 14.5 m, a displacement of 90,617 t and an engine power available for propulsion of 17,240 kW. The weather data covers the Atlantic ocean with a latitudinal and longitudinal resolution of 0.25°, a temporal resolution of 3 h and a fore-

Fig. 1 Transatlantic voyage of bulk carrier from Venezuela to the English Channel within 12 days. Left side shows result from graph algorithm and right from genetic algorithm including boundaries

cast range of 7.5 days. The described objective, constraints, variables, implementation in C++ and system settings are considered to allow direct comparison of both approaches regarding computation time and quality of results. To allow on-board voyage optimization an ordinary personal computer is used.

Comparison A scenario with a minimum speed of 5 kn, a maximum speed of 15 kn and a voyage duration of 12 days is solved using the A* algorithm. For the duration outside the forecast range, the shortest distance is assumed. The result shown in Fig. 1 is achieved in less than one hour. This scenario is used as baseline for comparison. The time consuming part of the computation is the calculation of fuel costs, hence the arc weights, due to the consideration of 130 neighbors described by latitude, longitude and time. Assuming a variable arrival time and a constant speed which eliminates the time discretization, the computation time is less than one minute. Halving the geographic resolution returns a result in 7% of the baseline computation time, while halving the geographic resolution and simultaneously doubling the temporal resolution requires approximately 50% of the baseline computation time. Distance and fuel costs differ by less than 5% compared to the baseline. As to the genetic algorithm, an initial population is given by the Great Circle Route (GCR) and an average speed of 13 kn. An upper (UB) and lower boundary (LB) are displayed in Fig. 1. ETA, minimum and maximum speed are the same as above. A population size of 20 and 30 variables describing route and speed profile results in the route shown in Fig. 1, but takes 37% more time than the baseline, thus more than one hour. Distance and fuel costs are almost equal to the baseline. Decreasing the number of variables to 18 reduces time by 30% compared to the baseline without impairing distance and costs. When setting the LB to the initial population the result is not acceptable as it does not resemble the minimum found with the A* algorithm or with the GCR as the initial population. The results are not improved when using LB, 18 variables and a population size of 50. Only increasing the population size to 100 results in a good output in this case, but this also leads to a seven times higher computation time.

Further tests regarding mutation rate, crossover mechanisms or other options would be interesting, but are not addressed in this study.

Discussion and Conclusions The graph algorithm is mainly influenced by the discretization in space and time. As expected, the results of the genetic algorithm strongly depend on initial population, population size and number of variables. A suitable initial population with a small number of variables provides sound results in adequate computation time, even at a rather small population size. However, when it comes to initial populations not close to the optimum, population size needs to be increased significantly implying a major rise in computation time. First, the optimum cannot always be predicted to set the initial population accordingly, but a variation of the initial population may contribute to decision support. Second, bearing in mind that updated weather forecasts can be provided e.g. every 6 h, computation time needs to be as short as possible. Consequently, due to more reliable results that do not depend as strongly on the input data, the graph algorithms is considered to be advantageous for the described problem and application.

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