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From Weather to Waypoints: Predicting Fuel Consumption and Optimizing Maritime Routes with ML and Graph Search

KATSOS P.[1], STOURAITI A.[1,*], VENTIKOS N.[1], THEMELIS N.[1], APOSTOLAKOS, G.[1], STAMATOPOULOU E.[1], TOLIOPOULOS T.[2] ,SKALIDI I.[3], GOUNARIS A.[2]

[1]School of Naval Architecture and Marine Engineering, National Technical University of Athens, Iroon Polytechneiou 9, Zografou, 15773, Athens, Greece

[2]School of Informatics, Aristotle University of Thessaloniki, University Campus, 54124, Thessaloniki, Greece

[3]School of Spatial Planning and Development, Aristotle University of Thessaloniki, University Campus, 54124, Thessaloniki, Greece

*corresponding author: Angeliki Stouraiti
e-mail: angeliki_stouraiti@mail.ntua.gr

Abstract: This paper introduces a framework for predicting ship fuel consumption and optimising routes by integrating physics-based models, machine learning (ML), and graph search algorithms. A synthetic dataset was generated using a physics-based resistance and propulsion model of a Kamsarmax bulk carrier under varying environmental conditions. A Multi-Layer Perceptron (MLP) was trained to forecast fuel consumption from this dataset. The model was then combined with a dynamic A* routing algorithm over a spatio-temporal graph of the Aegean Sea. Results reveal that this approach captures nonlinear ship-environment interactions and identifies fuel-optimal routes, reducing overall consumption compared to static methods. The study demonstrates the potential of physics-informed ML with adaptive routing for sustainable maritime transport.

Keywords: Fuel consumption prediction, Machine Learning (ML), Weather routing

1. Introduction

Fuel consumption is the primary operational expense in shipping and a significant source of greenhouse gas emissions. Precise prediction of consumption under varying weather and sea conditions is therefore vital for cost savings and decarbonisation. Recent advancements in machine learning (ML) enable the creation of data-driven models that capture nonlinear ship–environment interactions, while graph-search algorithms offer effective tools for voyage optimization. Combining these methods can enhance weather routing to make operations safer, quicker, and more sustainable.

2. Related work

Classical weather routing relies on deterministic ship models with shortest-path algorithms. Recent methods combine physics-based and data-driven techniques. Kytariolou and Themelis (2022) developed a MATLAB-based weather routing tool that uses a physics-based fuel consumption prediction model and genetic algorithms to minimise fuel consumption while adhering to safety constraints. Conversely, machine learning has been effectively applied to fuel prediction tasks. For instance, Xie *et al.* (2023)Xie et al. (2023) used models like XGBoost and Random Forest to estimate ship fuel consumption, achieving high accuracy ($R^2 \approx 0.9977$, MAPE $\approx$ 4%). These studies highlight the benefits of integrating physics-based and ML methods for maritime energy efficiency and routing.

3. Methodology

3.1. Methodology overview

The proposed framework (Figure 1) integrates physics-based modelling, machine learning, and graph search into a unified workflow. The process consists of six main steps: (1) definition of ship particulars and environmental conditions, (2) estimation of resistance, propulsion power and fuel consumption through a physics-based model, (3) generation of a synthetic dataset, (4) training and validation of a Multi-Layer Perceptron (MLP) regressor, (5) application of shortest path algorithms (Dijkstra and Dynamic A*), and (6) evaluation of fuel consumption and voyage efficiency.

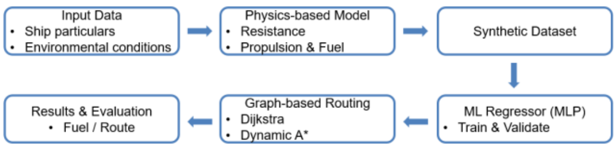

Figure 1. Methodology workflow

3.2. Problem formulation

The voyage optimization problem is formulated as a pathfinding problem over a discretized spatial-temporal domain. The area of interest is divided into grid cells, with time discretized into fixed intervals to capture evolving conditions. Ship trajectories are represented as paths through the grid, with transitions constrained by vessel kinematics and safety limits. The cost of each transition is defined in terms of fuel consumption predicted by the ML model. Formally, the objective is to find the least-cost path. The optimal route minimizes the cumulative cost while ensuring voyage feasibility.

3.2. Physical Method

A synthetic dataset was generated for use in the weather routing algorithm. This dataset was constructed using a physics-based model that estimates the fuel consumption of a Kamsarmax bulk carrier vessel (Table 1) that sails in the Aegean Sea.

Resistance was estimated by combining ITTC (calm water), Fujiwara (wind), and empirical formulas (wave). Propulsion power was derived using propeller–hull interaction coefficients and validated against the engine load diagram. Fuel consumption was computed from the engine SFOC map, and CO_2 emissions from standard emission factors. This dataset provided the basis for training the predictive ML model. For more details on the calculation procedure, see the work of Kytariolou and Themelis (2022).

3.3. Regressor

A Multi-Layer Perceptron (MLP) was selected for training on the synthetic dataset to predict daily fuel consumption due to its capability to achieve high prediction accuracy in regression tasks. (Hornik, Stinchcombe and White, 1989; Han *et al.*, 2021)

The model used two hidden layers (100 and 50 neurons), ReLU activation, and a stochastic gradient-based optimizer.

3.*4. Voyage Routing*

The routing problem is modelled as a pathfinding problem. Two strategies are compared: (1) Dijkstra with hourly replanning, and (2) Dynamic A*. The two strategies are based on a time varying ML-predicted fuel consumption grid. The first strategy transforms the grid into a graph and finds the shortest path in terms of minimizing fuel consumption. The second strategy is a spatio-temporal A* that searches over states, where each move to a neighboring grid-cell advances time by the prescribed step duration and incurs a cost proportional to the predicted fuel at that time and location, with a Euclidean heuristic guiding the search to minimize the total fuel over the voyage.

4. Results

The evaluation focused on a voyage from Piraeus to Chios in the Aegean Sea. Three performance metrics were compared: fuel consumption, voyage duration, and distance sailed. Results show that the Dynamic A* strategy clearly outperformed Dijkstra. While both methods resulted in the same voyage duration (10 hours), Dynamic A* achieved an 11.1% fuel reduction compared to Dijkstra (11.65 tons vs. 13.10 tons). In addition, the Dynamic A* route shortened the sailed distance from 160.21 NM to 144.98 nm.

Table 2. Summary of path metrics for the two routing strategies for the voyage Peiraeus-Chios

Method	Fuel [tons]	Duration [h]	Distance [nm]
Dijkstra	13.10	10	160.21
Dynamic A*	11.65	10	144.98

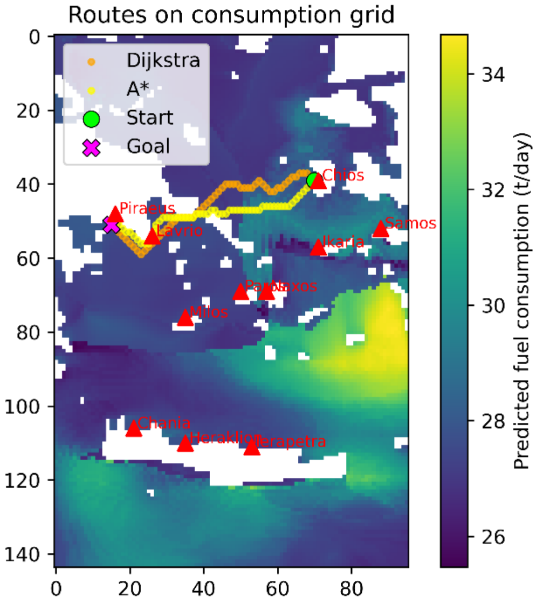

Figure 3. Recovered routes for the Peiraeus–Chios voyage with harbour markers and labels for reference

5. Acknowledgements

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