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Ship route optimization using hybrid physics-guided machine learning

To cite this article: Ulrik Jørgensen *et al* 2022 *J. Phys.: Conf. Ser.* **2311** 012037

Ship route optimization using hybrid physics-guided machine learning

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Abstract. This paper presents a method for energy efficient weather routing of a ferry in Norway. Historical operational data from the ferry and environmental data are used to develop two models that predict the energy consumption. The first is a purely data-driven linear regression energy model, while the second is as a hybrid model, combining physical models with data-driven models using machine learning techniques. With an established energy model, it is possible to develop a route optimization that proposes efficient routes with less energy usage compared to fixed speed and heading control.

1. Introduction

To support the UN's sustainable development goal of combatting climate change, the International Maritime Organization (IMO) has adopted mandatory measures to reduce ship emissions through the Ship Energy Efficiency Management Plan (SEEMP) (IMO, 2019). The initial IMO greenhouse gas (GHG) strategy is to reduce average CO2 emissions across the international shipping fleet by at least 40 % by 2030, and aiming towards 70 % by 2050, compared to 2008 values. The total annual GHG emissions from international shipping should be reduced by at least 50 % by 2050, compared to 2008. One manner to support this goal is through efficient voyage planning. To do so, the energy consumption of a vessel under various operational and environmental conditions must be estimated. By optimizing the route of the vessel with respect to the prevailing conditions, the energy consumption of the voyage can be minimized. Route optimization has the potential for significant reductions in energy consumption, where the associated cost and emission savings are estimated to be around 7 % for the global fleet [1].

1.1. Related work

As originally presented in [2], an overview of the state-of-the-art optimization methods used in weather routing has been presented in [3], while a weather routing system based on travel time, added resistance, and safety is developed in [4]. Many of the related works for weather routing revolve around long-distance route optimization where a large reduction in energy consumption can be achieved by avoiding the roughest environmental conditions. However, a considerable reduction of energy consumption can also be achieved for short-sea shipping, due to the high frequency of voyages. An example is presented in [5] where weather routing system for short-sea shipping is based on a pathfinding algorithm with the use of met-oceanographic predictions.

With large amounts of operational ship data and environmental data available, there has been an increased interest in using machine learning methods for estimating the energy consumption [6, 7, 8]. Often, regression models are used to predict the energy consumption, using engine RPM, ship velocity and weather data as inputs.

Machine Learning (ML) is being applied in a wide variety of domains due to its state-off-the-art performance in many classification and regression tasks. ML techniques are data-driven, i.e. they fit a model to a data set without explicit knowledge of underlying relationships. Applying such techniques in safety-critical systems can therefore be a challenge since ML models are often used as "black boxes", where the underlying causality is unknown. Facilitating trust in such methods is, therefore, a challenge, as the interpretability of ML models is limited. As a result, there is a growing consensus that ML techniques should be coupled with physical knowledge to strengthen and overcome some of the drawbacks with ML. This technique is called hybrid physics-guided ML (also referred to as knowledge-guided ML, science-guided ML, physics-guided ML, physics-informed ML, physics-aware AI, and theory-guided data science) and is gaining popularity within both the ML and scientific communities [9, 10]. Recently, several works have applied hybrid physics-guided ML, i.e., within the fields of air-foil aerodynamics [11] and energy fusion [12] with promising results.

1.2. Objective
The objective of this paper is to develop a weather routing system for a ferry that will propose the most energy efficient route. The accuracy of the weather routing system depends on the accuracy of the model used to predict the energy consumption (hereby referred to as energy model). In this paper, we seek to investigate if hybrid physics-guided ML techniques can prove useful when applied within the maritime domain. More specifically, we investigate if it is possible to estimate the energy consumption of a vessel more accurately using hybrid physics-guided ML techniques than using pure ML techniques.

1.3. Assumptions
When referring to energy consumption, we focus on the propulsion energy alone i.e., hotel loads are not considered. Moreover, passenger comfort is not included in the optimization schema, but low energy consumption is often correlated with low environmental disturbances, which in turn increase the comfort level. For the ferry route used in this work, transit is the longest and most energy consuming phase (75 % to 80 % of the overall propulsion energy used for an individual trip) with the most intricate interplay between vessel and environmental forces [2]. Consequently, we only focus on the transit phase in this paper. Finally, as this is a route suggestion optimizer, we do not consider dynamic traffic, since the captain will always be in direct control of the vessel.

2. Methodology
From the ship we gather GPS positions, speed over ground (SOG), course over ground (COG), vessel heading, power consumed by the electric motors driving the propulsors, and local wind measurements on the ship. In addition, vessel trim angle, and ship draft are measured, which often are not easily available. Draft measurements are gathered by mounting two displacement radars at the side of the ferry, measuring the distance between the sensors and the sea surface. Knowing the distance between the sensors, distance measurements from the two sensors are used to calculate the average draft measurement as well as vessel trim angle.

The ship data from about 1000 half hour ferry crossings is logged at a frequency of 1 Hz. Waves and current values are estimated by meteorological forecasting models gathered from the open-source weather service provided by MET Norway [13]. From the waves model we collect the wave period and the wave direction, measured from true north. From the current model we collect the speed and direction, relative true north. The weather models have a temporal resolution of one hour and a spatial resolution of 800 m × 800 m.

The waves and current models are interpolated in time and space to relate them to the ship data. Weather data are first interpolated spatially using inverse distance weighted interpolation with the four grid points closest to the current position. Then, the values are interpolated linearly in time. Directional variables, e.g. current direction, are interpolated in the space of complex numbers, mapping angles between 0° and 360° to the unit circle before interpolation.

To remove unphysical data, all trips are filtered by discarding trips that do not have a reasonable duration or speed profile. The stored data is used to develop the energy models, as illustrated in Figure 1.

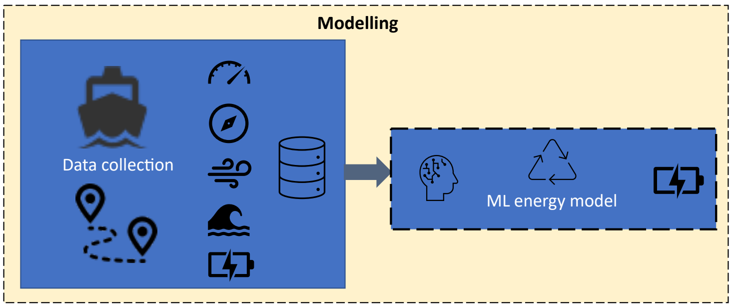

Figure 1: Collected data is used as input to the energy models.

2.1. *Data analysis*

This paper is a continuation of the work done in [2]. In this study, draft, trim and wind measurements are collected from the ship in addition to the other ship data. An analysis of the three newly added data is given in the following.

In this study, the static draft and trim are utilized. These values are estimated as the mean of the prior 30 s of data for each departure when the vessel is free floating and not affected by engine forces. In this way measurements are not affected by dynamic variations from external forces during the voyage. To remove measurement bias, all used measurements are scaled by subtracting the mean draft value for each sensor.

Having two draft measurements, one located at the front, and one located at the back of the vessel, the trim can be calculated using the draft measurements. Additionally, the pitch angle is measured by a vessel motion reference unit (MRU). The calculated trim is compared with the pitch angle. As can be seen in Figure 2, there is a high correlation (Pearson correlation coefficient $P = 0.97$) between calculated trim angle and the pitch angle. Moreover, since there is a high correlation between the pitch angle and the trim angle calculated using the draft measurements, we conclude that both signals are applicable as model input. For simplicity by keeping the number of inputs to a minimum, we choose to use the draft measurement to estimate trim angles.

The wind measurements from the vessel are compared with wind models from the weather service provided by MET Norway. Wind speed and direction analysis are shown in Figure 3 and Figure 4 with Pearson correlation coefficient $P = 0.76$ and $P = 0.49$, respectively. The level of correlation is as expected since wind measurements are often highly varying since it is affected by the vessel itself as well as measuring a combination of average and wind gusts.

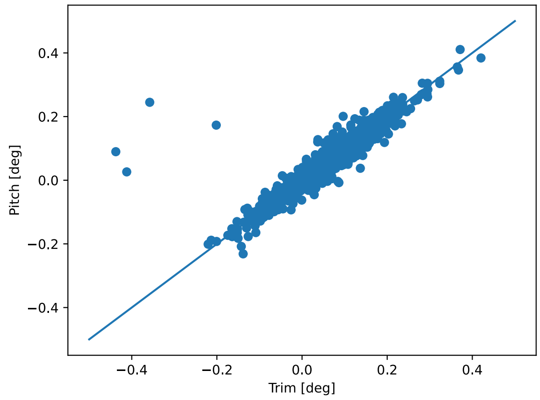

Figure 2: Correlation between calculated trim angle from the displacement radars and pitch angle from the vessel MRU.

Data from MET Norway on the other hand, is model based and does not capturing the complex dynamics around the vessel in the local area. Moreover, the measurement height is not the same as the MET Norway model. Nevertheless, since there are clear relationships between the wind measurements and the MET Norway model, we conclude that the vessel wind measurements are reliable and will therefore use these measurements in the energy model to capture the complex wind dynamics.

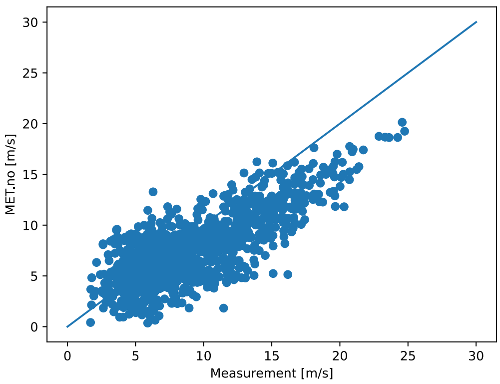

Figure 3: Correlation between measured wind speed and wind speed from MET Norway model.

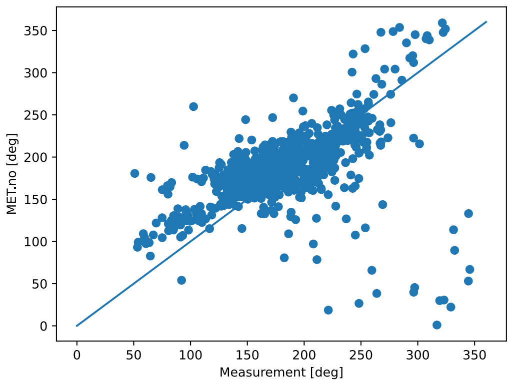

Figure 4: Correlation between measured wind direction and wind direction from MET Norway model.

2.2. Energy models
Using the collected weather and ship data, two energy models are developed and evaluated.

2.2.1. Linear model The first energy model is a linear regression model based on selected parameters derived from the collected data. These parameters are selected based on their correlation with the energy consumption. This model is purely data driven, where the correlation between the input parameters and the energy consumption are identified via ML.

To improve the linear model proposed in [2], vessel draft and trim measurements have been added to the energy model. To further improve the energy model, model parameters are expressed such that the correlation between them are minimized. For example, instead of using wave peak period ω_0 and the wave angle of attack β separately, the wave encounter frequency ω_e is used instead and given by

$$\omega_e = \left| \omega_0 - \frac{\omega_0^2}{g} U \cos(\beta) \right| , \tag{1}$$

where g is the acceleration of gravity and U is the speed of the vessel. Moreover, the current velocity $v_{c,rel}^n$ relative the vessel operating at velocity v_v^b, is given by

$$v_{c,rel}^b = R_n^b(\theta) v_{c,true}^n - v_v^b, \tag{2}$$

where $v_{c,true}^n$ is the current velocity relative true north, θ is the vessel heading, $R_n^b(\theta)$ is the rotation matrix between the vessel body attached frame $\{b\}$ and the North-East-Down (NED) frame $\{n\}$. Superscript $\{b, n\}$ denotes which frame the vector is expressed in. See (Fossen, 2021) for details.

Based on the relationships above, a regression model for the transit phase is developed. The model estimates energy per distance used during transit based on average SOG, longitudinal and transverse current and wind speed, wave encounter frequency, significant wave height H_s, trim and draft.

2.2.2. Hybrid physics-guided model As an extension to the linear model, a hybrid physics-guided model combining physical models with data driven ML models is developed (hereby referred to as hybrid energy model). The model utilizes known physical relations between the selected parameters and the energy consumption. Machine learning methods are then applied to find the unknown relations.

The transverse (denoted t) and longitudinal (denoted l) wind (denoted w) and current (denoted c) forces $F_{i,j}$ acting on a vessel are estimated as

$$F_{i,j} = \frac{1}{2} \rho_i A_{i,j} v_{i,j} \left| v_{i,j} \right| , \tag{3}$$

where $i \in \{w, c\}$, $j \in \{t, l\}$, ρ_i is the air and water density, $A_{i,j}$ is the transverse and longitudinal air and underwater cross-section areas and v_i is the relative wind and current velocities. For modelling simplicity, the static cross-section areas are given by the vessel drawings, hence we do not consider dynamic cross-section areas due to time varying trim and draft. The drag coefficients in Equation 3 are not included, as they are assumed to be estimated as part of the ML-based regression.

In addition to the linear model parameters presented in Section 2.2.1, squared SOG, wind and current forces given in Equation 3 have been added to the physics-guided ML model.

3. Optimization

Once the energy models have been sufficiently trained and evaluated, they can be used to optimize planned routes. This is illustrated in Figure 5. Given the trained energy model, an initial route, weather forecast, and ferry schedule, the goal of the Route Optimizer (RO) is to return an optimized route that minimizes the energy consumption. The RO optimizes the route by modifying the geography and speed profile of the initial route.

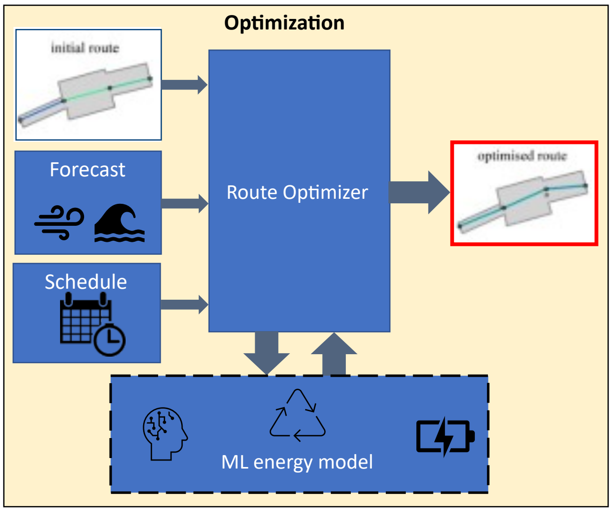

Figure 5: Optimization flow diagram.

The initial route, shown in the upper left corner of Figure 5, is typically defined as a collection of waypoints from the start position to the desired end position of the voyage. The legs between two consecutive waypoints are then often associated with a desired speed value and a cross track distance where it is safe for the vessel to operate. In fact, this is so common that there exists a standard route plan exchange format (RTZ) specifically for this purpose [14, 15]. The cross-track distances for all the legs in a route constitutes a safety zone the vessel can safely operate in, illustrated as the grey area around the routes in Figure 5. The safety zone will typically be configured to avoid shallow water and fixed obstacles. This area also set an absolute limit for where the route optimizer can manipulate the voyage route.

Another element that constrains the route optimizer is the ferry time schedule. The ferry typically needs to be at the destination within a required time. The schedule sets an upper bound for the duration of the trip, and the route optimizer must balance the arrival time with the energy consumption since these are in general competing parameters.

The final input to the RO is the trained energy model presented in Section 2.2. The energy model will be used to estimate the energy consumption for the current proposed route by the RO. To score the current route, the RO proposes an objective function for the current route as a sum of the energy estimation, penalty terms, and regularisation terms. Given the objective function score, the RO can iteratively update the route until an optimal route is given. For details about the optimization, please see [2].

4. Result and discussion

Energy consumption is a sensitive parameter for operating companies, hence the presented data has been anonymised by removing explicit reference to location and energy consumption is not reported in absolute numbers, but relative to reference values, e.g. the average energy consumption for the route or the energy consumption before optimisation.

To evaluate model performance, the data set was split into training and test sets. In this manner, the models can be evaluated on unseen data, i.e. the test set. The test error of both models is given in Table 1, where the mean error of the predictions is evaluated as a percentage of the true values. Furthermore, the root mean squared error (RMSE) and coefficient of determination (R^2) are evaluated.

In [2], the mean error of the energy model was found to be 7 %. By utilizing the improved linear model in this study, the error has decreased to 5.44 %. As such, it appears that the

Table 1: Model accuracy metrics.

	Training error [%]	Test error [%]	Test RMSE [$\frac{\mathrm{kW\,h}}{\mathrm{m}}$]	Test R^2
Linear model	4.86	5.44	0.0024	0.79
Hybrid model	4.26	4.70	0.0020	0.86

outlined parameter selection and transformation yields a more accurate energy model.

The second model investigated was a hybrid model that leverages known physical relationships. In this manner, classical physics-based models can be fused with data-driven ML-based models. Furthermore, non-linearity is added to the model via such relationships. The hybrid model was found to have superior performance, with a mean error of 4.70 % for the test set. Furthermore, the RMSE was found to be 0.002 kW h/m, with an R^2 value of 0.86. This indicates that the model can describe most of the variation in the data with high accuracy. It should be noted that the accuracy and generalizability of ML-models will increase for larger data sets. As such, the accuracy of the models can be expected to increase further given more data.

Figure 6 shows the predicted energy consumption (y-axis) plotted against the true energy consumption (x-axis) of the linear model (blue dots) and hybrid model (orange dots). If a model is zero error, the dots will appear along the diagonal line, indicating that the predicted energy equals the true energy.

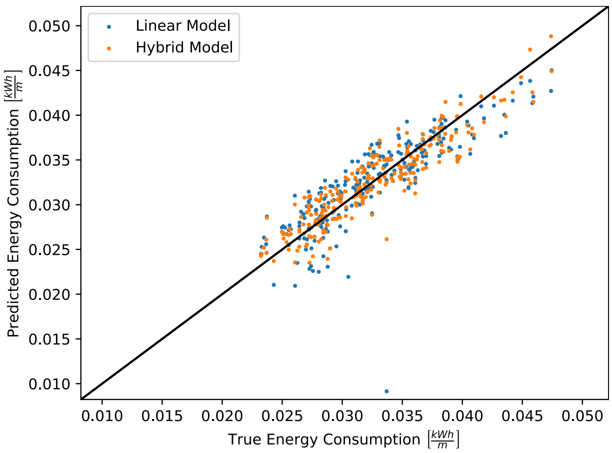

Figure 6: Energy model predictions on test set.

The results indicate that the hybrid model is more robust with respect to predicting energy consumption, as the data are more concentrated about the line representing zero error. Furthermore, the figure shows that the linear model has several outliers, indicating that the linear model was not able to capture the true relationships in the data set. This may be due to the inherent inability of a linear model to capture nonlinear physical relationships. In addition, the model may be overly sensitive to certain parameters, where anomalous values in the input parameter space result in erroneous predictions. It appears that the hybrid model could handle such data in a better manner. This may be due to its ability to leverage the known physical relationships between parameters in a better manner, making it less sensitive to outliers, and thus more generalizable. Hence, it is of interest to investigate the sensitivity of the models to various input parameters, to better understand what the respective models are focusing on.

4.1. Model interpretation

Generally, machine learning models are viewed as black boxes, where end-users have little to no insight into the reasoning behind a prediction. By providing a form of explainability to the model, users may gain increased confidence in the models [16].

Figure 7 and Figure 8 illustrate the scaled mean energy contributions of the input parameters for the linear model and hybrid model respectively. These contributions are calculated as the mean of all energy contributions derived from each parameter irrespective of sign. In this manner, the relative energy contribution of each parameter can be compared, yielding insight into the reasoning behind the models.

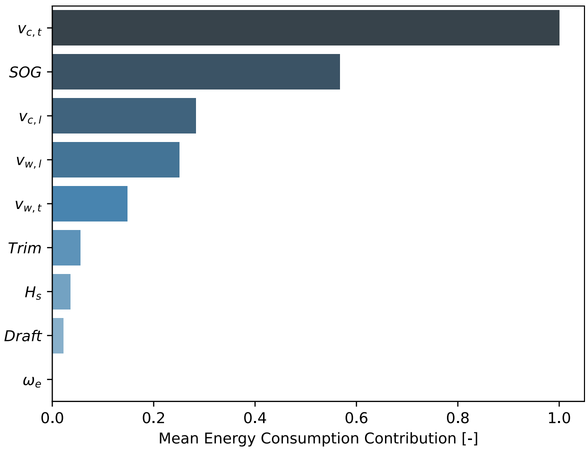

Figure 7: Relative mean energy contributions of the linear model.

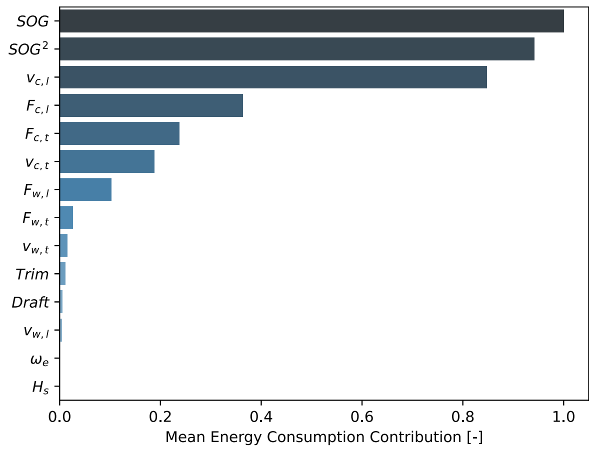

Figure 8: Relative mean energy contributions of the hybrid model.

From Figure 7 it is evident that the linear model has focused primarily on the relative transverse current speed, $v_{c,t}$, as well as the speed over ground. From a physical standpoint, the relationship between SOG and energy is sound. However, the focus of the model on the relative transverse current speed does not seem physically meaningful. It may be attributed to the dominating current direction in the region in which the ferry is operating. As such, the model may be indirectly able to identify the direction in which the ferry is sailing. Each direction the ferry sails will constitute a specific operational mode, due to the varying characteristics of each route. As such, the model may focus on differentiating between these modes, as this minimizes the prediction error. This, however, may come at the expense of the generalizability of the model. This is supported by Table 1, which illustrates the training and test error of the investigated models. The difference between the performance of the linear model on the training and test data sets are higher than that found for hybrid model, which may indicate overfitting to the training data.

Figure 8 shows that the primary focus of the hybrid model is on speed related parameters, with current forces as secondary contributions, and wind contributions as tertiary contributions. Furthermore, the contributions of the longitudinal components of the respective external forces appear to have a higher magnitude than their transverse components. This is conducive with physical phenomena related to ship resistance. As such, the model appears to be physically meaningful. The relative longitudinal current speed, however, has a more significant contribution than expected. This may be due to correlation with the speed over ground.

In both the linear and hybrid models, the trim, draft, significant wave height and wave encounter frequency parameters provide limited to no contribution to the predicted energy consumption. Such results are unexpected, as these parameters are known to affect ship resistance. However, when inspecting the data, it was found that the draft varies little between trips. Such low variation in the data set likely results in the inability of the ML model to learn meaningful correlations. Furthermore, as seen in Figure 2, the observed trim angles in the data set are small. From a physical standpoint, it follows that there should be little to no energy contribution from such angles. Similarly, the wave related parameters have little effect on the energy models, despite wave resistance constituting a significant portion of the energy consumption of sea-going vessels. This can be explained by the region and season the data were gathered in, where the wave height was generally low with little variation, i.e. less than 1 % of the vessel length. As such, the model is unable to learn any meaningful relationship between the wave related parameters and energy consumption, as other effects are dominant.

In general, it appears that the use of a hybrid model provides multiple advantages compared to a purely data-driven linear model. In addition to achieving better accuracy, the hybrid model behaves in a manner that conforms to known physical relationships. As such, the causation of the model is more apparent, increasing confidence in the predictions. The linear model, being purely data-driven, appears to focus more on correlations in the data than physical relationships founded in causation. Furthermore, the hybrid model introduces known non-linear relationships that allow the model to learn more complex relationships than a linear model.

It should, however, be noted that the developed models are specific for this ferry and will need to be re-trained for another vessel and/or region. The focus of the models may also shift depending on the use case. For instance, draft, trim and wave related parameters may play a larger role for vessels that experience greater variation. Also note that by specifying the wave encounter frequency as in (1), one do not get any information how the wave direction affects the energy. For cases with larger H_s this could influence the model performance and should be investigated further. Nonetheless, hybrid ML-based energy models should generally outperform linear ML models due to their ability to leverage more complex causal relationships, as well as be more generalizable.

4.2. Optimization
Once an energy model has been trained on the operational data of the vessel, it can be utilized for route optimization, as illustrated in Figure 5. In this study, the hybrid energy model was chosen for use due to its enhanced performance. To investigate the performance of the route optimization, a historical voyage was randomly selected from the data set. This test voyage can then be optimized, and the relative energy consumption of the respective routes compared.

Using the test voyage, the operational data were extracted and input to the route optimization function. The test voyage is input as the initial route, along with the prevailing met-ocean conditions for the voyage. The original, unoptimized route is illustrated in blue in Figure 9. Using the safety zone, illustrated in green, as a constraint, the route optimization outputs an optimized route, illustrated in orange. Note that the optimized route is slightly longer than the original, but provides an energy reduction of 3.7 %. The optimization algorithm therefore finds a longer path which is advantageous for the current met-ocean conditions. The energy reduction is achieved solely via minor alterations to the route and speed profile prior to departure. If implemented, such route optimizations can lead to a reduction in fuel consumption and associated operational costs.

5. Conclusion
In this paper, a linear regression, and a hybrid physics-guided ML energy model have been developed to facilitate route optimization. The models were developed to predict the energy consumption of a ferry based on operational data. Compared to the data-driven linear regression model, the hybrid model was found to have superior results. Furthermore, by attempting to

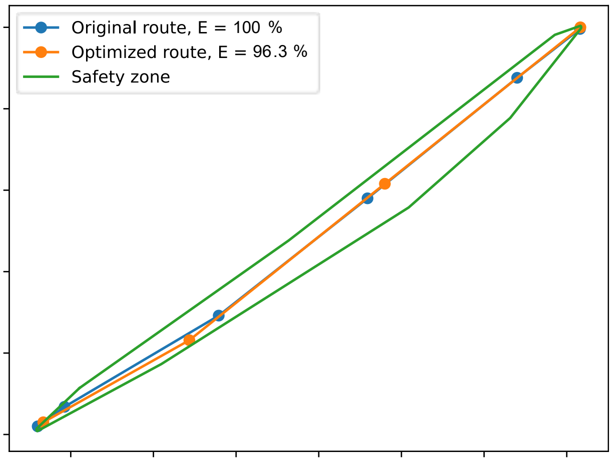

Figure 9: Example figure showing optimized route, energy savings and safety zone.

interpret the reasoning behind the models, it appeared that the hybrid model discovered causal relationships grounded in known physical relationships. The linear model, however, appeared to discover correlations without direct causality.

Based on the findings, the hybrid energy model was tested in an optimization schema showing an energy reduction of 3.7 % compared to the actual consumption, simply by applying minor route and speed profile alterations. Such route optimizations prior to departure can lead to reduced fuel consumption and operational costs.

Acknowledgments

The work presented here is in part funded by the Norwegian Research Council (NRC) through the project Self-learning route optimization for ships (SMARTSHIPROUTING), NRC project no. 295763. The authors would like to thank the project owner Norwegian Electric Systems and the project partners HAV Design and Havila Kystruten. Furthermore, we would like to thank Fjord1 for allowing us to collect operational data from one of their ferries.

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