Data-Driven Explainable Artificial Intelligence for Energy Efficiency in Short-Sea Shipping

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Abstract. The maritime industry is under pressure to increase energy efficiency for climate change mitigation. Navigational data, combining vessel operational and environmental measurements from onboard instruments and external sources, are critical for achieving this goal. Short-sea shipping presents a unique challenge due to the significant influence of surrounding landscape characteristics. With high-resolution onboard data increasingly accessible through IoT devices, appropriate data representations and AI/ML analytical tools are needed for effective decision support. The aim of this study is to investigate the fuel consumption estimation model's role in developing an energy efficiency decision support tool. ML models that lacking explainability may neglect important factors and essential constraints, such as the need to meet arrival time requirements. Onboard weather measurements are compared to external forecasts, and our findings demonstrate the necessity of eXplainable Artificial Intelligence (XAI) techniques for effective decision support. Real-world data from a short-sea passenger vessel in southern Sweden, consisting of 1754 voyages over 15 months (More of data description and code sources of this study can be found in the GitHub repository at https://github.com/MohamedAbuella/ST4EESSS), are used to support our conclusions.

Keywords: Short-sea shipping · Energy efficiency · Explainability · Spatio-temporal aggregation

1 Introduction

Maritime transport of commercial freight is widely considered as one of the most environmentally friendly modes of transportation due to its low emissions of greenhouse gases (GHGs) per unit of capacity and distance traveled. This can result in a reduced carbon footprint and a smaller impact on the global climate, as illustrated in Fig. 1a. Short-Sea Shipping (SSS) represents a mode of commercial transportation that does not involve intercontinental cross-ocean

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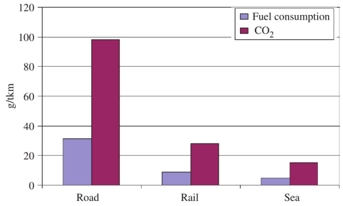
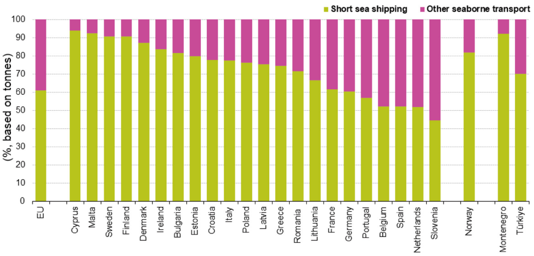
travel. SSS provides a cost-effective and eco-friendly alternative by leveraging inland and coastal waterways to transport commercial freight. The statistics presented in Fig. 1b demonstrate the vital role SSS plays in Europe [11].



(a) Average environmental impact of different transportation modes per tonne-kilometer (in terms of fuel consumption and CO_2 emission) [18].



(b) European short-sea shipping of freight versus total sea transport, in 2021 [11].

Fig. 1. The importance of short-sea shipping for Europe.

Despite the advantages of sea transportation for the environment, there remains a significant need to improve the energy efficiency of sea vessels. The SSS continues to produce negative effects on natural habitats and contributes to air pollution along the coasts of populated cities [10]. Therefore, the International Maritime Organization (IMO) has conducted numerous studies, recommended standards, and imposed policies for the maritime sector aimed at reducing carbon dioxide (CO_2) emissions by 40% by 2030 and cut overall GHG emissions by 50% by 2050, compared to the levels from 2008 [6].

Furthermore, the COVID-19 pandemic has accelerated the digitalization of the global shipping industry, drawing significant attention to data collection and preparation stages [8]. Information on select operational and environmental conditions can be obtained from Automatic Identification System (AIS) messages, a service established by the IMO in 2002. AIS was designed to record the sensor measurement data and transmit vessel position information for communication between ships and neighboring shores [13].

While sea transportation boasts a lower carbon footprint compared to other modes of transportation, there is still improvement potential. However, it requires a significant effort to understand and enhance the energy efficiency of sea vessels and how to reduce their negative impact on the environment. One potential approach to achieving this objective is through employing data analytics and Machine Learning (ML) techniques to study vessel operations and quantify the influence of various factors, such as weather and sea conditions, on fuel consumption. This work is a result of collaboration between academia and a Swedish startup company CetaSol AB[1]. CetaSol has developed iHelm, an intelligent digital analytical platform for energy optimization tailored toward small

[1] https://cetasol.com/.

and medium-sized vessels. The platform features a data logging and processing unit installed on board and a user interface that provides the captain with relevant visual information and real-time actionable insights for optimal operation. Land-based personnel can access an analytical cloud platform with statistics and reports, enabling them to make informed decisions and optimize operations over time. The ultimate goal is to assist shipping companies in reducing their operating costs, increasing profitability, and minimizing environmental impact.

In this paper, we report our findings related to one aspect of this multifaceted issue: the creation of fuel estimation and prediction algorithms. We believe this work offers several contributions to the scientific community, including: (1) the investigation of various models for fuel consumption estimation, forming the foundation and the first step toward an energy efficiency decision support tool; (2) quantifying the relative importance of pertinent factors and the benefits of data aggregation from various onboard and external sources; (3) showcasing the practical application of eXplainable Artificial (XAI) in the iterative improvement of the ML model, based on real-world considerations; and (4), illustrating the potential to enhance short-sea vessel energy efficiency by employing real-world data from a passenger vessel operating in southern Sweden over a period of 15 months.

With these contributions, our study lays the groundwork for future research in the area. Also, shipping companies can leverage the insights and recommendations presented in this paper. The lessons learned from our experiments will contribute to the optimization of shipping operations and the reduction of adverse environmental effects. Moreover, integrating these innovative insights into upcoming fleet management systems will empower SSS companies to gain a deeper understanding of vessel operations and make well-informed, data-driven decisions to reduce costs. The remainder of the paper is organized as follows: related work is described in Sect. 2. Section 3 introduces the case study and the challenges linked to short-sea shipping. The outcomes of modeling and energy efficiency analysis are covered in Sect. 4. Finally, conclusions and future work are addressed in Sect. 5.

2 Related Work

As digitalization and automation become increasingly prevalent in the maritime sector, the research addressing new challenges has been growing rapidly, particularly with regard to developing frameworks for energy efficiency and Maritime Situational Awareness (MSA) in cross-ocean shipping. On the other hand, the research progress has not kept pace for vessels operating in coastal areas. Thus, this literature review will focus on our primary area of interest, which is research that is related to short-sea shipping.

Recent research studies [9,14] have explored energy-efficient routing for an electric ferry in Western Norway. They rely on operational data from onboard measurements and environmental conditions from the Norwegian Meteorological Institute, interpolated to the nearest temporal and spatial resolutions of the vessel's onboard data. Similarly, the researchers from Napa Ltd. in Finland conducted several studies on voyage optimization, including two cases [12,20] where environmental conditions were collected from the weather forecasts. Other studies in the literature have also processed environmental data from different weather providers to match the vessel's operational onboard data, as reviewed in [22]. However, such approaches do not account for weather factors that influence both fuel consumption and the Estimated Time of Arrival (ETA), which is a crucial constraint when optimizing the vessel's voyage, especially in SSS.

The maritime industry increasingly adopts digitization and Machine Learning (ML) techniques; however, their black-box nature remains a significant challenge. While ML can provide valuable insights, the reasoning behind the predictions made by such models is often difficult to comprehend due to their lack of explainability. To address this issue, Shapley additive explanations (SHAP) [17] were developed, providing a way to determine the contribution of each input feature toward the model's output. SHAP is commonly used as a solution to the explainability issue in ML. A recent study [16] analyzed feature importance for the power consumption of a chemical tanker. The results indicate that the ship's speed through the water is the most influential feature, while ship heading and other weather features have relatively minor influences. Kim et al. [15] utilized SHAP in combination with an anomaly detection algorithm to detect and interpret anomalies in onboard data from a cargo vessel. It allowed the identification of the specific sensor variable responsible for an anomaly, and SHAP-based clustering was used to interpret and group common anomaly patterns. A validation study for explainability in the maritime time-series data [21] compared two common model-agnostic XAI approaches, SHAP for a global method and LIME as a local method. A literature review on XAI [7] discusses the importance of XAI as a key component in modern AI techniques. The authors present a taxonomy of existing contributions related to the explainability of different machine learning models. Overall, the use and development of ML techniques in the maritime industry requires a careful balance between performance gain and explainability.

3 Case Study Description

Throughout this paper, we will focus on a specific use case of a passenger ferry operating in southern Sweden. The ship's name is Buro, built in 1985, with a carrying capacity of 68 Gross Tonnage, a length of 19 m, and a breadth of 6.41 m. It operates daily passenger traffic between Swedish islands Öckerö, Kalvsund, Framnäs, and Grötö in the Gothenburg archipelago. A single voyage takes approximately 30 min, with an average speed of 8.2 knots (4.2 m/s). The picture of the vessel is provided as in Fig. 2. Additional information about the ship and its voyages can be found on Marine Traffic website [5].

The ship's onboard data have been received using an IoT system designed and developed by CetaSol in Gothenburg, Sweden. The data has been gathered over a period of 15 months, between January 2020 and March 2021. The majority of signals are collected at 3 Hz frequency and record key navigational parameters

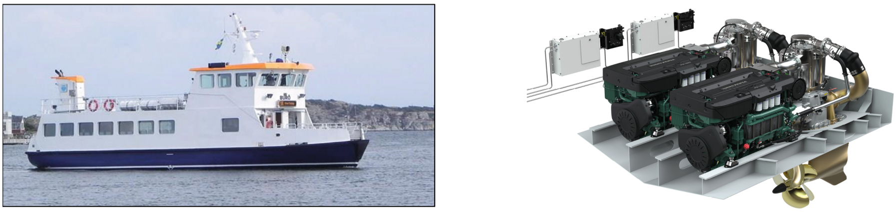


Fig. 2. The passenger ship Buro (photo by Owe Johansson [5]) and her diesel engine from Volvo Penta [2].

such as the ship's position, course (direction), and speed; operational parameters such as fuel rate, engine speed, torque, and acceleration; and meteorological data such as apparent and real wind speed and direction.

Additionally, external weather variables such as wave height and speed and direction of both wind and sea current have been collected from external APIs, Copernicus Marine Service [1] and Stormglass [4]. The complete list of available signals is included in the supplementary material[2].

Onboard signals have been resampled from the original 3 Hz frequency to a 1-min time resolution. The external weather data are past forecasts (hindcasts), which have been interpolated from an hourly temporal resolution to a 1-min temporal and a 0.25 to 0.5° spatial resolution. Trilinear interpolation has been applied in time and space dimensions.

3.1 Problem Formulation

From a broad perspective, improving the vessel's energy efficiency for fuel savings and lowering GHG emissions can be done in two stages. The first is during the design, where the shape, materials, and equipment are decided – which is out of the scope of this paper. The second stage is during the ship's operation, both on the water and at ports. The latter, however, is heavily influenced by the former; it is, therefore, challenging to design optimal operation upfront, before fully understanding how each individual vessel behaves [23].

ML-based solutions present an opportunity to leverage domain knowledge and customize it to specific usage patterns and design choices. Our study embraces this approach specifically for short-sea shipping, which exhibits distinct challenges from those encountered in deep-sea shipping.

Continuing with the illustrative case of the Buno passenger ferry, the actual profiles of fuel consumption are illustrated in Fig. 3. In the middle, we showcase (sorted) fuel consumption per voyage on one day, 1^{st} of April 2020. On the left and right, respectively, we show on the map the best and worst voyages, with

[2] Due to the limited length of the paper, the complete supplementary material is provided in the GitHub repository at:https://github.com/MohamedAbuella/ST4EESSS.

color-coded speed (upper) and fuel rate (lower). Finally, at the bottom, we show environmental conditions: wind, current, and waves.

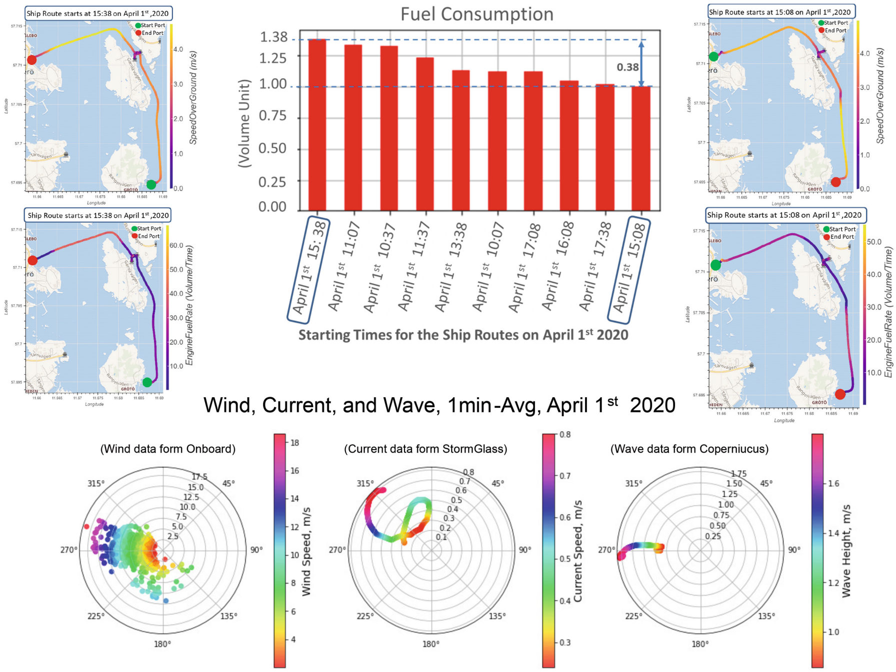


Fig. 3. Vessel's fuel consumption and some navigational data on April 1st, 2020

Notably, the highest fuel consumption voyage started at 15:38; in the final part of the route, Buro is traveling toward the west, against the wind, current and wave directions. This can be compared to the previous voyage, at 15:08, going in the opposite direction – which also happens to be the most fuel-efficient. At the same time, the vessel's speed was also relatively high when traveling westward; in such harsh conditions, the captains tend to overcompensate, unsure about the exact speed profile needed to keep the timetable, and knowing that "catching up" may not be possible due to physical limitations. Thus, at this combination of vessel speed, direction, and weather conditions, the vessel's resistance has increased, leading to 38% higher fuel usage. One can clearly see that the weather impacts fuel consumption significantly, and that there is room for improvement using ML-powered decision support.

In particular, we envision a decision support system that provides a vessel captain with, in real-time, suggestions on the most efficient operation, including vessel trajectory and speed profile. Such a system requires an accurate fuel estimation model capable of counterfactual reasoning, i.e., analyzing the effect a change in speed or direction would have on the overall fuel consumption. By adapting the operation to varying external conditions, the decision support system can thus improve the overall energy efficiency of the vessel.

4 Modeling and Analysis

In this section, we describe the workflow for estimating fuel consumption, which is the first stage of energy efficiency modeling and analysis for an SSS vessel. Figure 4 shows the workflow. Details on the framework, results, and discussion are provided below.

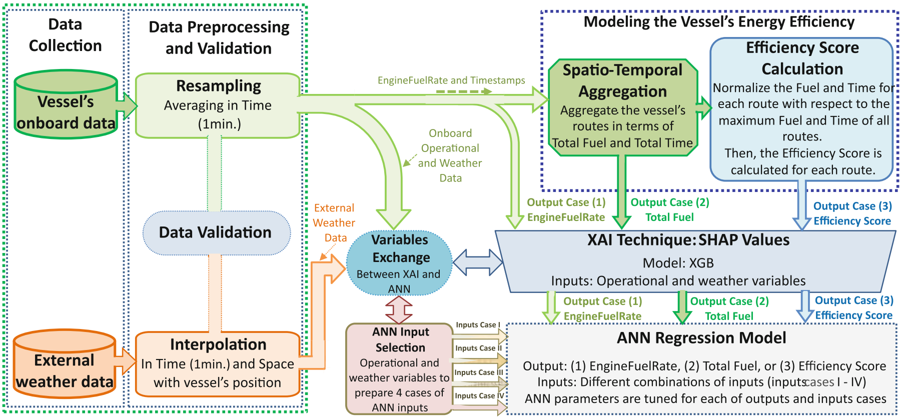


Fig. 4. Workflow of modeling and analysis of energy efficiency in short-sea shipping

4.1 Exploratory Analysis

As a starting point, an Extreme Gradient Boosting (XGBoost) model is initially deployed as a regression model for estimating fuel consumption. The XGBoost model is chosen for its ease of use and minimal need for parameter tuning, making it ideal for exploratory analysis. The navigational variables, as listed in Table 1, are used as inputs to the model. The first model created uses EngineFuelRate directly from onboard data as the regression output, which is the most intuitive case. The initial performance of the model, even without any additional tuning, is relatively good, with an R^2 value of 0.7615.

In the next step, the Shapley additive explanations (SHAP) [17] technique was used, employing the SHAP package, which is publicly available in Python [3]. These SHAP values were used to determine the importance value of each feature to the overall regression accuracy. This highlights the strengths of the XGBoost algorithm since calculating SHAP values for tree-based models is relatively fast compared to many other regression approaches. However, during this stage, a

Table 1. The navigational variables and their data sources.

Variable	Name	Source	Variable	Name	Source
Vo_1	Latitude	Onboard	Vc_1	WindSpeed_cps	Copernicus
Vo_2	Longitude	Onboard	Vc_2	WindDirection_cps	Copernicus
Vo_3	SpeedOverGround	Onboard	Vc_3	WaveHeight	Copernicus
Vo_4	HeadingMagnetic	Onboard	Vc_4	WaveDirection	Copernicus
Vo_5	Pitch	Onboard	Vs_1	WindSpeed_sg	Stormglass
Vo_6	Roll	Onboard	Vs_2	WindDirection_sg	Stormglass
Vo_7	WindSpeed_onb	Onboard	Vs_3	CurrentSpeed	Stormglass
Vo_8	WindDirection_onb	Onboard	Vs_4	CurrentDirection	Stormglass

significant issue was observed with the initial model. The vessel's motion (kinematics) variables such as SpeedOverGround, Pitch, and HeadingMagnetic (direction), were found to be more significant in determining fuel consumption compared to factors such as weather variability.

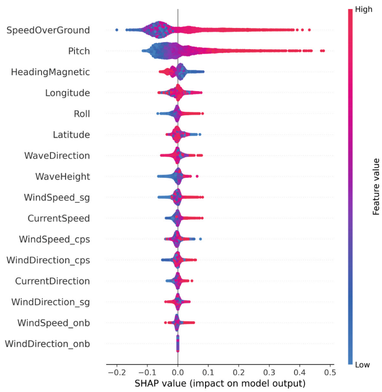
Figure 5 depicts Beeswarm plots for Shapley values for the XGBoost model, considering the three output cases investigated in this section. The SHAP values are used to determine the contribution of features to the regression model and are often visualized using such beeswarm plots. Ranking features based on their SHAP values allows interpreting how the changes in feature values affect the model estimations.

In the case of the first model, predicting EngineFuelRate, depicted in the top-left of Fig. 5, vessel kinematics were found to be the primary drivers. While such a model may be suitable for explanatory analysis, it cannot be used for optimization and counterfactual estimations.

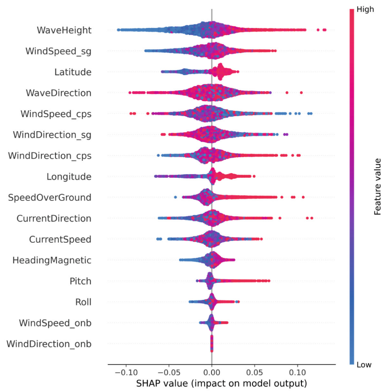
Therefore, the insights gained from XAI and SHAP values indicate the need to change our approach. Relying solely on the R^2 score is not sufficient in evaluating the usefulness of a regression model. We require a model that is less dependent on kinematics and considers weather variables as more impactful. SHAP values, as an explainable AI tool, enable us to gain more insights into the weaknesses of the developed fuel consumption model and guide future improvements.

To address the limitations of the initial model, and based on the insights obtained, the second model uses an aggregated output of Total Fuel for the entire voyage, instead of instantaneous EngineFuelRate. The performance of the Total Fuel model is similar and also relatively good, with an R^2 value of 0.8400. on the other hand, the SHAP values reveal that weather variables, particularly the waves and the wind from external sources, are much more important. This model is much better at capturing their causal relationships with fuel consumption.

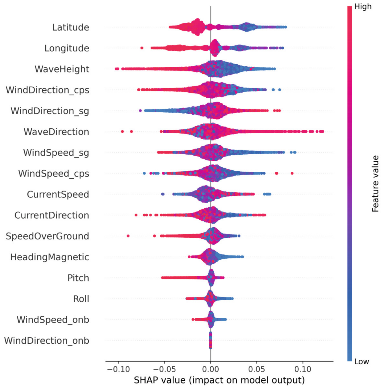
The SHAP values reveal that the second model is more suitable for energy efficiency analysis since it captures known causes for high or low fuel consumption, making it more useful for counterfactual reasoning. This model can answer



(a) Model's output is EngineFuelRate, (R^2=0.7615)



(b) Model's output is Total Fuel, (R^2=0.8400)

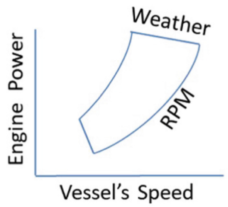


(c) Model's output is Efficiency Score, (R^2=0.8324)

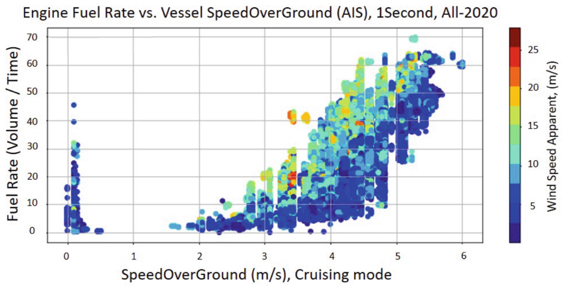
Fig. 5. Beeswarm plots of SHAP values for XGBoost regression model with different outputs

questions like "what would be the effect of changing the speed profile on a particular voyage," which the first model cannot. At the same time, an issue remains that prevents it from being practical as a part of an energy efficiency decision support tool. This issue arises from the strong relationship between fuel consumption and vessel speed, as illustrated in Fig. 6. The trend indicates that higher cruising speeds result in higher fuel consumption. As a result, if this model is used as part of a speed profile optimization tool, it will likely recommend only one solution: to lower the speed. While a correct decision from a pure fuel perspective, it is not practical since the ferry must keep its timetable.

To address the practical limitations of the second model, we introduce a new metric called the Efficiency Score. This metric aims to balance fuel consumption



(a) Theoretical analysis of sea vessel's engine operation.



(b) Vessel Buro's actual engine performance.

Fig. 6. A fuel efficiency curve: how the fuel consumption varies as a function of speed.

and time of arrival, two critical factors in determining energy efficiency for SSS vessels. Only by considering both factors together, can we represent the vessel's overall energy efficiency. The efficiency Score is defined as follows:

$$\mathrm{Eff}_{\mathrm{Score}} = 1 - \frac{2 \times Fuel \times Time}{Fuel + Time}, \quad (1)$$

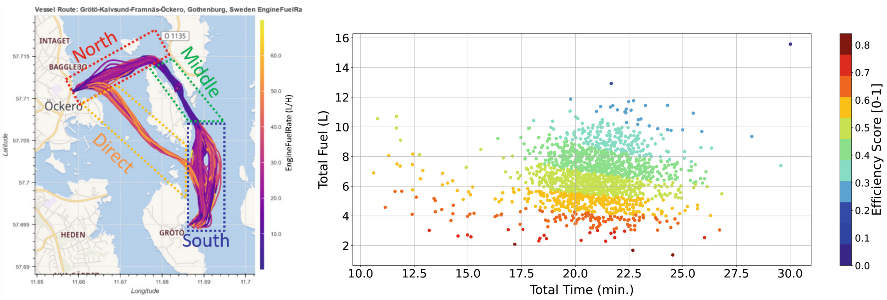
where $Fuel$ and $Time$ are the normalized total fuel and time, respectively, for each route of the vessel. The accumulated fuel is derived from the raw onboard EngineFuelRate data, while the accumulated time is based on the SpeedOverGround measurements and the distance traveled. The distance between two points is calculated using the Haversine formula [19], which takes into account the Earth's spherical shape.

Figure 7 illustrates the spatio-temporal aggregation for the vessel's routes. First, in Fig. 7a, we show the routes in spatial dimensions (latitude and longitude). Next, we project these routes as aggregated Efficiency Scores onto new dimensions of fuel and time Fig. 7b. The plot confirms the Efficiency Score correctly captures the original intuition, with voyages that have lower fuel and shorter time having higher Efficiency Scores, and vice versa.

As a result, in our final regression model, we use the Efficiency Score as the output variable, reaching R^2 score of 0.8324. The corresponding SHAP values plot, shown at the bottom of Fig. 5, indicated that spatial variables, namely latitude and longitude, are the most important factors in estimating fuel consumption over time. The model also suggests a causal relationship between fuel consumption and weather variables, with external weather variables being more significant than vessel motion.

4.2 Optimizing the Model

After completing the exploratory analysis, we aim to optimize the performance of the model by switching from XGBoost to Artificial Neural Networks (ANN).



(a) The vessel routes are mapped by latitude and longitude.

(b) The routes are projected by aggregated Efficiency Score in dimensions of fuel and time.

Fig. 7. The vessel routes and their projections as Efficiency Scores.

Table 2. Description of the four input cases of ANN.

Inputs Case	Operational Variables	Weather Variables	
		onboard data	external sources
I	Vessel's location, speed, and direction are used for all cases	wind	—
II		—	wind, wave, and current
III		wind	wave and current
IV		wind	wind, wave, and current

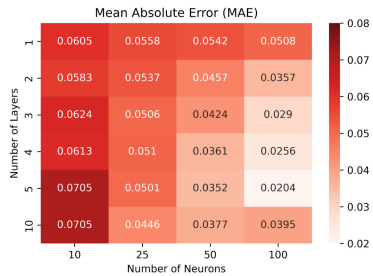
Through several experiments involving the various relevant combinations of navigational variables, as depicted in the workflow diagram in Fig. 4, we obtain models with higher performance than XGBoost, albeit at the cost of increased computational complexity.

The first step in optimizing the model is to identify the best set of input parameters. We consider four cases of ANN inputs, where each case consists of different combinations of operational and weather variables. Further details about these ANN input cases are provided in Tables 2 and 3. It is worth noting that some operational variables, such as pitch and roll, are highly correlated and primarily depend on the vessel's speed and weather conditions. Therefore, we have excluded such inputs from our ANN models. In general, the vessel's speed and direction are the most important control variables used to improve energy efficiency.

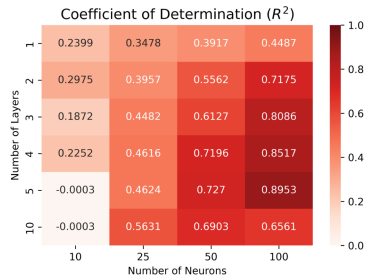
According to the workflow in Fig. 4, we consider the same output cases for the ANN models as we did for XGBoost: EngineFuelRate, Total Fuel, and Efficiency Score. We optimize the structure of the ANN models using a grid search approach, considering the four different input cases and three output cases, resulting

Table 3. Combinations of variables that are used in the four input cases of ANN. The names and sources of these variables can be found in Table 1.

Inputs Case	# Inputs	List of Inputs
I	6	Vo_1, Vo_2, Vo_3, Vo_4, Vo_7, Vo_8
II	12	Vo_1, Vo_2, Vo_3, Vo_4, Vc_1, Vc_2, Vc_3, Vc_4, Vs_1, Vs_2, Vs_3, Vs_4
III	10	Vo_1, Vo_2, Vo_3, Vo_4, Vo_7, Vo_8, Vc_3, Vc_4, Vs_3, Vs_4
IV	14	Vo_1, Vo_2, Vo_3, Vo_4, Vo_7, Vo_8, Vc_1, Vc_2, Vc_3, Vc_4, Vs_1, Vs_2, Vs_3, Vs_4



(a) Results in MAE for ANN Structure Search



(b) Results in R^2 for ANN Structure Search

Fig. 8. Grid search results for the best ANN structure, with Efficiency Score output.

in twelve ANN models being tuned separately. To measure the estimation accuracy of the different ANN models, we adopt three metrics: root mean squared error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2).

The heatmaps in Fig. 8 show that the best ANN structure for the Efficiency Score model is achieved with 100 neurons and 5 layers, as it results in the lowest value of MAE and the highest value of R^2. These heatmaps also show that the model's performance is sensitive to changes in the hyperparameters, indicating the importance of carefully tuning the ANN model to achieve optimal results.

Tables 4, 5, and 6 present the results of all twelve ANN regression models. The fourth case of inputs (IV), which considers operational and weather variables from onboard and external sources, led to the best performance (i.e., $R^2 = 0.8088$ and $MAE = 0.0516$) for estimating EngineFuelRate, as shown in Table 4.

On the other hand, for estimating both Total Fuel and Efficiency Score, the best is the combination of inputs for case (II), including the weather variables only from external sources. The former achieves $R^2 = 0.9170$ and $MAE = 0.0221$, as shown in Table 5, and the latter $R^2 = 0.8953$ and $MAE = 0.0204$ (Table 6).

Table 4. Results of ANN with EngineFuelRate output, for different input cases.

Input Cases	Number of ANN Inputs	Number of ANN Layers	Number of ANN Neurons	RMSE	R2	MAE
I	6	10	100	0.0852	0.7153	0.0631
II	12	4	100	0.0730	0.7909	0.0544
III	10	5	100	0.0714	0.8001	0.0531
IV	14	4	100	**0.0698**	**0.8088**	**0.0516**

Table 5. Results of ANN with Total Fuel output, for different input cases.

Input Cases	Number of ANN Inputs	Number of ANN Layers	Number of ANN Neurons	RMSE	R2	MAE
I	6	4	100	0.0980	0.2074	0.0776
II	12	5	100	**0.0317**	**0.9170**	**0.0221**
III	10	5	100	0.0562	0.7398	0.0409
IV	14	5	100	0.0351	0.8986	0.0249

Overall, ANN models outperform XGBoost in terms of all three estimation metrics across all three outputs. At the same time, the results clearly demonstrate the importance of incorporating external weather forecasting sources – the onboard weather information is not sufficient.

The accuracy of the Total Fuel and Efficiency Score models is higher compared to the EngineFuelRate model's estimation. The Total Fuel model yields the highest accuracy, whereas the Efficiency Score model, which takes into account the total time of the vessel's routes, only shows a slight difference.

4.3 Exploiting the Model

The Beeswarm plot in Fig. 5c indicates that the vessel's location has the most significant impact on the Efficiency Score. Therefore, a spatial analysis was conducted to identify the impact of various combinations of operational and weather variables on the Efficiency Score concerning the vessel's location.

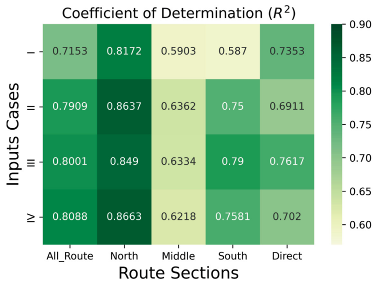
As shown in Fig. 7a, we partitioned the vessel's typical route into four distinct sections, namely North, Middle, South, and Direct. The impact of operational and weather combinations on fuel consumption varies in these sections.

The results are shown as heatmaps in Fig. 9, revealing that the direct route from south to north or vice versa, located on the open sea, is particularly susceptible to the impact of weather conditions. Thus, for this direct section of vessel routes, the estimation of Efficiency Score, as shown in Fig. 9b, has the highest accuracy with different inputs combinations.

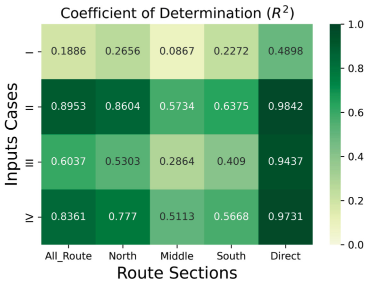
Meanwhile, in the north section, where strong either head or tail wind is more frequent (in this area, west winds dominate) with respect to the vessel route, the Efficiency Score estimation has the second highest accuracy, as in Fig. 9b.

Table 6. Results of ANN with Efficiency Score output, for different input cases.

Input Cases	Number of ANN Inputs	Number of ANN Layers	Number of ANN Neurons	RMSE	R2	MAE
I	6	3	50	0.0807	0.1886	0.0634
II	12	5	100	**0.0290**	**0.8953**	**0.0204**
III	10	4	100	0.0564	0.6037	0.0431
IV	14	5	100	0.0363	0.8361	0.0267



(a) EngineFuelRate



(b) Efficiency Score

Fig. 9. Results (R^2) for ANN regression with EngineFuelRate and Efficiency Score as outputs across different input cases in relation to varying vessel's route sections.

In the other case, when it comes to estimating EngineFuelRate, as shown in Fig. 9a, the results are not accurate. For instance, the direct sections of the route are not achieving the highest accuracy, even though they are supposed to experience more weather conditions than other sections due to these sections being the most similar to an open sea.

5 Conclusion

By using a practical real-world example of a small passenger vessel, this paper showcases how XAI with ML techniques can facilitate decision-making. In this case, we analyze the process of developing a fuel estimation module, which is a crucial component of the vessel's energy efficiency decision support tool. The outcomes presented in this paper have the potential to enhance operation and energy management in short-sea shipping.

Based on the discussed results, it is evident that the proposed approach of aggregating data and estimating the Efficiency Score, instead of directly working with the EngineFuelRate onboard signal, is more effective in facilitating decision-making. The resulting model is based on a more comprehensive understanding of the critical factors that impact fuel consumption, both temporally and spatially, resulting in more dependable counterfactual predictions. Moreover, the quantitative evaluation indicates that estimating the Efficiency Score produces more precise and less biased outcomes than estimating the measured EngineFuelRate.

Moving forward, the developed model will be integrated with the vessel's energy optimization framework to provide decision support to captains on suitable trajectories and speed profiles based on current and forecasted weather conditions, thereby enhancing energy efficiency. Real-world implementation and the evaluation of its value for short-sea shipping are planned in the near future.

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