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Fuel consumption prediction models for different types of bulk carriers based on historical voyages, meteorological data and vessel characteristics

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***Résumé* – La prédiction de la consommation de carburant des navires est un élément clé pour l'industrie du transport maritime pour se conformer aux réglementations de l'Organisation Maritime Internationale sur les émissions. Cette étude propose deux approches visant à prédire la consommation de carburant des vraquiers en se basant sur les données historiques des voyages et de la météo en plus des caractéristiques physiques des navires. Les résultats obtenus montrent que les modèles ont pu prédire une proportion significative de voyages avec un pourcentage d'erreur inférieur à 5% lorsque l'on compare la consommation totale de carburant réelle et prédite tout au long de chaque voyage. Les approches proposées permettront de prédire avec précision la consommation de carburant pour une meilleure planification des itinéraires des navires.**

***Abstract* – Predicting the fuel consumption of ships is a key element for the shipping industry to comply with International Maritime Organisation regulations regarding emissions. This study proposes two approaches to predict the fuel consumption of bulk carriers based on historical voyages, weather data and physical characteristics of ships. The results obtained show that the models were able to predict a significant proportion of voyages with an error percentage lower than 5% when comparing actual and predicted total fuel consumption throughout each voyage. The proposed approaches could accurately predict the fuel consumption for a better planning of the routes of the ships.**

***Mots clés* - Routage météorologique, navires vraquiers, consommation de carburant, apprentissage automatique.**
***Keywords* – Weather routing, bulk carriers, fuel consumption, machine learning.**

1 INTRODUCTION

The climate question is in the spotlight every day around the world. Today, the effects of climate change are becoming more apparent, such as rising average and extreme temperatures, altered precipitation patterns, thawing permafrost, and increased frequency of severe weather events. While maritime transportation is generally considered a cleaner mode of transportation compared to other modes, it is also facing increasing pressure to reduce its greenhouse gas (GHG) emissions.

Since 2018, the International Maritime Organization (IMO) has adopted a strategy to reduce GHG emissions from ships at its Marine Environment Protection Committee. This strategy aims to decrease the carbon intensity of international maritime transportation by at least 40% by 2030, compared to levels in 2008, and to lower total annual GHG emissions by at least 50% by 2050, also compared to 2008 levels [International Maritime Organization, 2018]. As part of this strategy, and since January 2020, a new regulation has been imposed reducing the limit of sulfur content in fuel oil from 3.5% to 0.5%. The IMO's GHG strategy establishes a timeline and framework for deciding when to consider various policies, and includes a list of potential short-, medium-, and long-term policy measures. The proposed measures can be divided into three categories: technological measures, operational measures, and market-based measures.

The Ship Energy Efficiency Management Plan (SEEMP) proposed by the IMO as an operational measure offers several features for optimizing fuel efficiency through operational changes. One of the key features of this management plan is the ship weather routing. This is defined by [Simonsen et al, 2015] as the process of determining the optimal course and speed for a ship's voyage based on various factors including nautical charts, forecasted sea conditions, the captain's expertise, and the specific characteristics of the ship. The use of weather routing has been shown to reduce fuel consumption by up to 3% [Armstrong, 2013] and, therefore, reduce CHG emissions, as it helps to identify the most efficient speed for a voyage, which can minimize fuel consumption, improve energy efficiency, and ensure the safety of the ship, crew, and cargo. Effective fuel consumption management is a crucial part of this process, as fuel costs make up a significant portion of a ship's operating expenses [World Shipping Council, 2008]. Reducing fuel consumption can lower operating costs and increase the overall efficiency of the ship.

A literature review by [Zis and al., 2020] has been conducted on weather routing and voyage optimization in maritime shipping. The authors provided a comprehensive overview of the main methodological approaches used in the field and identified the key disciplines that address this problem. The review demonstrates that the majority of the studies in this area are focused on either minimizing fuel consumption or reducing sailing time. Among the 40 relevant works reviewed in this literature survey, only five studies ([Hagiwara, 1989], [Hagiwara and Spaans, 1987], [Kobayashi et al., 2011], [Prpić-Oršić et al., 2014] and [Szlapczynska, 2015]) have taken into account ocean currents in addition to wind and waves when optimizing weather routing in maritime shipping. In order to minimize fuel consumption in the context of weather routing, it is necessary to have an estimation of its value beforehand, in addition to considering meteorological factors. This is difficult due to the different internal and external factors affecting this value and the absence of a linear relationship between all these factors.

A recent literature review presented by [Fan et al., 2022] has covered research on ships' fuel consumption models (SFC) published between 2011 and 2021. This literature review classified SFC models into three categories: the white box model (WBM), the black box model (BBM) based on data analysis, and the grey box model (GBM). The WBMs are based on mechanism analysis, in which fuel consumption is essentially modeled according to the principle of the ship-engine-propeller and the law of resistance transfer ([Yan et al., 2021]). The BBMs are statistical and machine learning models that require a large amount of data to capture the relationship between fuel consumption and the rest of the available factors. The most accurate Statistics-based models for predicting fuel consumption, according to [Uyanik et al., 2020], are Bayesian ridge regression, nuclear ridge regression, multiple regression, and ridge regression. The last type is GBMs, which combine WBMs and BBMs through a semi-mechanical formula and semi-data-driven model. This review of literature has brought attention to areas where research on fuel consumption prediction is lacking. Out of the 24 articles that were analyzed, only [Tran, 2021], [Isıklı et al., 2020], and [Fan et al., 2020] focused on bulk carriers while the rest were centered on container ships. Additionally, the fuel consumption prediction models developed in these three articles are limited to a single ship, and only [Fan et al., 2020] accounted for meteorological factors that have a significant impact on fuel consumption. Therefore, the models that have been developed are not applicable to diverse ship types operating in varied weather conditions.

The aim of this study is to contribute to this research gap by proposing predictive models of fuel consumption that are not reliant on data from a single ship, but rather on a large dataset comprising of 1254 ships of various physical characteristics, with a specific focus on bulk carriers. The proposed models will be integrated into a commercial weather routing system to optimize ship routing, not only in terms of cost and time of arrival, but also taking into account safety, emissions, and weather considerations. This research will propose a multiple linear regression (MLR) model and a mathematical model for predicting ship fuel consumption, which will be constructed using historical voyage data, weather data, and vessel characteristics data.

The structure of this paper is as follows. Section 2 describes the proposed methodology, which includes the problem formulation, data preprocessing, and proposed models. Section 3 presents a summary of the results obtained from the study. Finally, the conclusion of the paper is conducted in Section 4.

2 METHODOLOGY

The methodology (Figure 1) of this study includes the following main steps:

- Problem formulation: We present the problem and the research objective in this step.
- Data understanding: We provide an overview of the main parameters and data sources in this stage.
- Data preprocessing: We clean and transformed the raw data to make it suitable for analysis and modeling.
- Modeling: We present the models proposed, including the input parameters.
- Evaluation: We evaluate the models based on their errors per voyage and across the entire dataset.

2.1 Problem formulation

Accurately predicting fuel consumption is a significant challenge in the shipping industry, as it is influenced by a

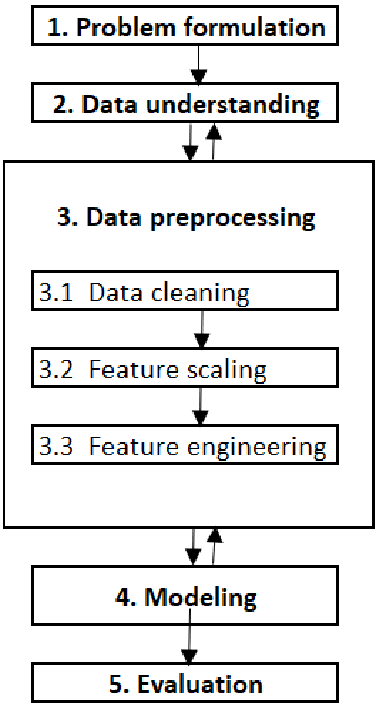

Figure 1: Overview of the methodology

variety of internal and external factors. Our study is based on data collected by our industrial partner from the so-called noon-reports. The ship captains send these reports every 24 hours with information on the status of the ship, including the remaining fuel level and speed. In addition, our data contains weather reports on meteorological conditions reported every 6 hours. Our objective is to use this information to develop models that take into account not only the speed of the vessel but also the weather conditions, the differences in the frequency of noon-reports and weather reports, and the different physical characteristics of the ships.

2.2 Data description

The present study is mainly based on historical voyages for the development of fuel consumption prediction models. At each point of the voyage of a given vessel, we have data on the identification of the vessel, its location, its speed over ground (SOG), its speed over water (SOW), the revolutions per minute (RPM) of the engine and the remaining level of each type of fuel: Intermediate Fuel Oil (IFO) and Marine gas oil (MGO). In addition, our data contains the direction and the speed/height of the wind, waves and currents at each point of the passage. From these, our industrial partner's analysts calculate the resulting speed loss for each meteorological component based on it's added resistance [Kim et al, 2017]. This speed loss will combine the meteorological information, the speed and the type of vessel into a single value that we denote by the wind/wave/current factor.

2.3 Data preprocessing

2.3.1 Data cleaning

Data cleaning is a crucial step that significantly impacts data analysis and prediction models. In this study, we followed a two-step approach for data cleaning. Firstly, we removed null values from the fuel consumption data, as ships are expected to always consume fuel during voyages. Additionally, we employed a commonly used statistical method for the identification and removal of outliers which is the z-score outlier detection. This technique calculates the deviation of each point in the dataset from the mean according to the following relationship:

$$z = \frac{x - \mu}{\sigma}$$

Where x is the data point, μ is the mean of the dataset, and σ is the standard deviation of the dataset. Outliers are defined as data points whose z-score exceeds a predetermined threshold. In our study, we used a threshold of 3, which corresponds to data points that are three standard deviations away from the mean of the dataset. By using this threshold, we identified only extreme values as outliers, in accordance with commonly used practices in the field of statistics and data analysis.
In addition to the outliers, it is necessary to detect voyages with abnormal or unexplainable behavior (Figure *2*). For this, we referred to a classical relationship often used in the literature [Bialystocki and Konovessis, 2016]. This relation links the sailing speed (v) to the fuel consumption (F) through the exponent (n), that depends on the type of the vessel, and is expressed as follows:

$$F(v) = \lambda v^n \text{ where } \lambda > 0,\ n > 0,$$

Several voyages were analyzed using this relation in addition to the knowledge of our industrial partner. Indeed, the training of this relationship on all our voyages showed some voyages with a negative coefficient λ and thus a non-conforming behavior since the fuel consumption and the speed follow the same trend. Other voyages with anomalous values of speed or fuel consumption at certain noon-reports were also detected. These detected voyages have been removed from our dataset for a better quality of modeling.
The different methods used in the cleaning process affected approximately 12% of the voyages. While this may seem like a significant loss of data, it was necessary to ensure the accuracy and reliability of the remaining data for analysis and modeling.

2.3.2 Feature scaling

At this stage, we made a change that is necessary for our models later on. Indeed, since the features affecting the fuel consumption have different ranges of values, we chose to bring them all to a single range, between 0 and 1. This technique

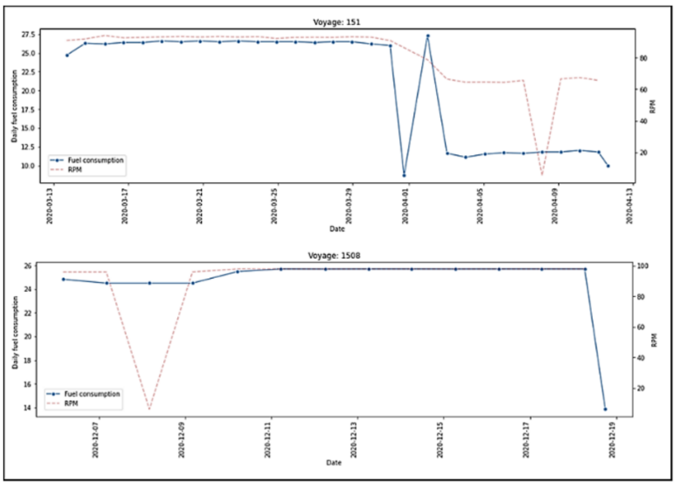

Figure 2 (Top): Voyage with a significant decrease in fuel consumption (blue) in the last 10 days and an outlier in RPM (red). Figure 2 (Down): Voyage with outliers in RPM and in fuel consumption

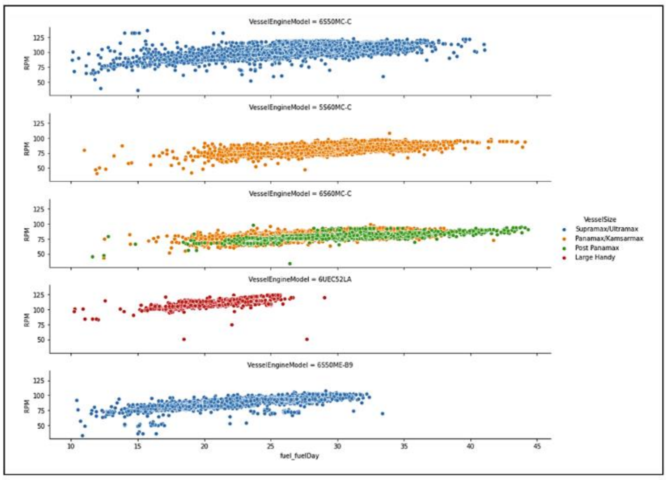

Figure 3: RPM and fuel consumption for each engine model and for each vessel size

commonly used in preprocessing is called the Min-Max scaling and performed according to the following relationship:

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where x_n is the normalized value corresponding to the original variable x, with a minimum and maximum value of x_{min} and x_{max}, respectively.

2.3.3 Feature engineering

At the feature engineering phase, we transformed our data to prepare it to the modeling step. To achieve this, we created new features. The first feature is the daily fuel consumption that we calculated from the remaining level of each fuel type (IFO and MGO). Additionally, we added the average speed loss over 24h resulting from each one of the three meteorological components (wind, waves and currents).

Moreover, since our study is based on developing a model that involves several bulk carriers, we proceeded to their categorization. Despite the fact that our study is focused on bulk carriers and that they have the same basic design and purpose, they do not have the same behavior during sailing and under different meteorological conditions. Therefore, we used scatter plots (Figure 3) to correlate RPM speed with daily fuel consumption, allowing us to identify distinct vessel categories based on similarities in behavior for each vessel size (Panamax, Post-Panamax…) as well as for each engine model. Vessels with similar behaviors were grouped together within the same category.

2.4 Modeling

2.4.1 Multiple linear regression models

Our first proposal builds upon the work presented in [Hajli et al., 2023]. The later uses a multiple linear regression (MLR) model to address a similar issue as our current study. However, the predictions made by that paper are limited to a specific set of sister-ships with similar physical characteristics. Our objective is to extend these predictions to other types of bulk carriers. To accomplish this, we utilized the following relationship from [Hajli et al., 2023] to train our model on each category of bulk carriers:

$$P = \sum_{v \in V} (\alpha_v + \beta_v S^3) + \gamma_1 W + \gamma_2 A + \gamma_3 T + \varepsilon \qquad (1)$$

This relationship links the daily fuel consumption P to the RPM speed S of each vessel v, the average daily speed loss caused by wind W, waves A and currents T.

The MLR model will fit the relationship (1) to data, minimize the error ε, determine the regression coefficients $\alpha_v, \beta_v, \gamma_1, \gamma_2$ *and* γ_3, and generate the estimated regression function $f_c(S, W, A, T)$ for each ship category c as follows:

$$f_c(S, W, A, T) = \sum_{v \in V_c} (w_{v,c} + u_{v,c} S_c^3) + \delta_{1,c} W + \delta_{2,c} A + \delta_{3,c} C \qquad (2)$$

Where, $w_{v,c}$ and $u_{v,c}$ are estimated for each vessel v of each category c and represent the intercept and RPM weight, respectively. The estimated weights for winds, waves, and current factors for each category c are denoted as $\delta_{1,c}$, $\delta_{2,c}$ and $\delta_{3,c}$, respectively.

The final estimated regression function to predict the daily fuel consumption is presented as follows:

$$f_c(S, W, A, T) = w_c + u_c S_c^3 + \delta_{1,c} W_c + \delta_{2,c} A_c + \delta_{3,c} T_c \qquad (3)$$

Where, for each category c, we have:

$$w_c = \frac{1}{|V_c|} \sum_{v \in V_c} w_{v,c} \quad \text{and} \quad u_c = \frac{1}{|V_c|} \sum_{v \in V_c} u_{v,c}$$

2.4.2 Mathematical model

Our study proposes a second fuel consumption prediction model that approximates the daily fuel consumption of bulk carriers. In this section, we define the set of parameters and decision variables defining this model.

Let V be the set of voyages, I the set of noon-reports provided by captains of ships, I_v the subset of noon-reports concerning the voyage $v \in V$ and J_i the set of weather reports in the noon-report $i \in I$. Each noon-report $i \in I$ contains information on the fuel consumption f_i and the RPM speed S_i. Also, each weather report $j \in J$ reports the speed loss caused by winds W_j, by waves A_j and by currents C_j.

We have used a number of variables in the formulation below. Specifically, x_1, x_2, x_3, x_4 and x_5 that refers to the weights of the RPM speed, the speed loss by winds, the speed loss by waves and the speed loss by currents, respectively. We also define a slack variable ϵ_v for each voyage $v \in V$. The optimization model is then presented as follows:

$$Min \sum_{v \in V} \sum_{i \in I_v} \left(f_i - \left(\sum_{j \in J_i} [x_1 S_i^3 + x_2 W_j + x_3 A_j + x_4 c_j] \frac{1}{|J_i|} \right) \right)^2 + \sum_{v \in V} \left(\frac{1}{|I_v|} x_5 \epsilon_v \right)^2$$

$S.t$

$$\sum_{i \in I_v} f_i = \sum_{i \in I_v} \sum_{j \in J_i} (x_1 S_i^3 + x_2 W_j + x_3 A_j + x_4 C_j) + x_5 \epsilon_v, \quad \forall v \in V$$

The objective is to minimize the quadratic error between the actual fuel consumption per 24h and the approximated one for

the entire voyage. The approximated fuel consumption is obtained by summing the RPM speed at each noon-report and each weather component at each weather report. We divide the sum by the number of weather reports to have one approximated fuel consumption.
The constraint assures that the total real fuel consumption per voyage is equal to the approximated one or as close as possible.

2.5 Evaluation

In order to assess the accuracy of our predictions and validate our models, we relied on a set of performance measures often used in the literature, namely mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). These types of errors were computed for each voyage in order to have insight into the distribution of errors over all voyages.

3 RESULTS AND DISCUSSION

Our study proposes two approaches to approximate fuel consumption of bulk carriers. The first is to train an MLR model for each category using average daily meteorological data as inputs. This results in a fuel consumption prediction equation for each category. The second proposal is a mathematical model that takes into account all the meteorological reports, subject to a constraint on the total fuel consumption for each voyage. This model can be trained on each category, but in the present study, we have chosen to train it on all categories together, due to the stability and strength of this kind of models. This approach gives a single fuel consumption prediction equation for all types of bulk carriers in the dataset.
Our models were trained using a dataset of 7754 voyages sailed by 1 254 different bulk carriers. Once the appropriate weights for each feature were determined, the models were evaluated on a separate, independent test dataset of 1 275 voyages, sailed by 535 different bulk carriers, that were not used during training.
To assess the accuracy of the models, we calculated in the first place the MAE, RMSE and MAPE errors for each voyage in the test dataset. By plotting the distributions of these errors, we can visualize the spread of errors over all voyages. The test results of the MLR models (Figure 4) show that they were able to predict the fuel consumption of 85,6% of the voyages with a MAE error of less than six metric tons per day (MT/day) and 84% of the voyages with a RMSE error of less than six MT/day. For the mathematical model, the test results (Figure 5) show that the fuel consumption of 84 % of the voyages was predicted with a MAE error of less than six MT/day and 82% of the voyages had the fuel consumption predicted with a RMSE error less than six MT/day. Regarding the MAPE error, the MLR models were able to predict 84.1% of the voyages with an error level below 20%, while for the same rate, the mathematical model was able to predict 82% of the voyages.

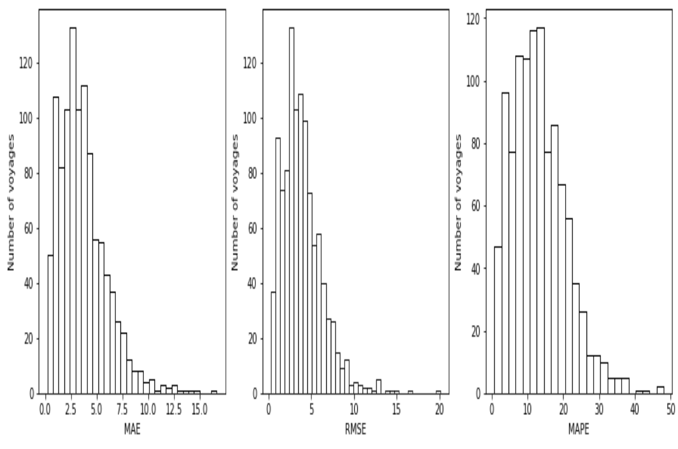

Figure 4: The distribution of MAE, RMSE and MAPE errors of the MLR models for voyages.

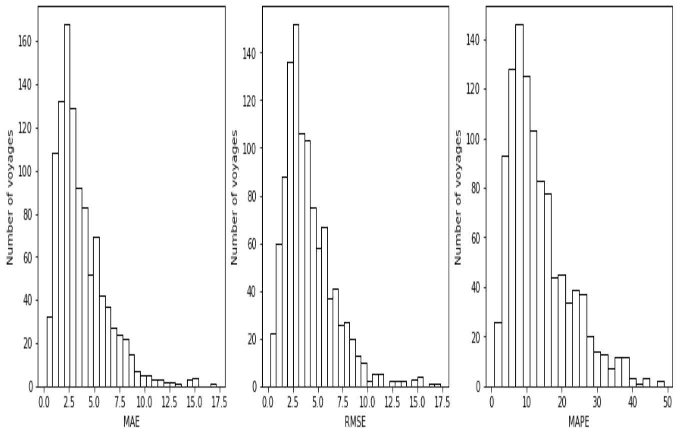

Figure 5: The distribution of MAE, RMSE and MAPE errors of the mathematical model for voyages.

In addition to the MAE, RMSE and MAPE errors calculated for each voyage, the residuals (Figure 6) of the two approaches were calculated at the level of each point of the dataset, and thus at the level of the daily reports (noon-reports), according to the following relation:

$$Residual_i = f_i - \hat{y}_i \quad (4)$$

where f_i is the recorded fuel consumption at the point *i* and $\hat{y}_i$ is the predicted fuel consumption at the same point. The distribution of the residuals from the noon-reports appears nearly symmetrical around zero for our models. Furthermore, by excluding outliers, the residuals between the reported and predicted daily fuel consumption are limited between -10 and +10 MT/day. However, the mathematical model's residual density is more focused around zero in comparison to the MLR models, highlighting the improvement that has been attained.
Since the residuals of noon-reports for a given voyage can be negative or positive and thus cancel each other out for the entire voyage, it is important to consider the residuals between the total reported and predicted fuel consumption per day for each voyage which are calculated as follows:

$$Residual_v = \sum_{i \in I_v} (f_i - \hat{y}_i) \quad (5)$$

where f_i is the recorded fuel consumption at the noon-report *i* of the subset I_v of noon-reports of the voyage *v*, and $\hat{y}_i$ is the predicted fuel consumption at the same noon-report. Since the total fuel consumption for a given bulk carrier on two voyages can be different depending on several factors (duration of the voyage, weather conditions, captain's behaviour...), we have chosen to compute the percentage of residuals between the total reported and predicted consumption for each voyage *v* and not only the residuals of (5), according to the following relation:

$$(Percentage\ residual)_{\ v} = 100 \times \frac{\sum_{i \in I_v} (f_i - \hat{y}_i)}{\sum_{i \in I_v} f_i} \quad (6)$$

The distribution of the error percentages (Figure 7) shows that 76% of the voyages have an error level between the reported and

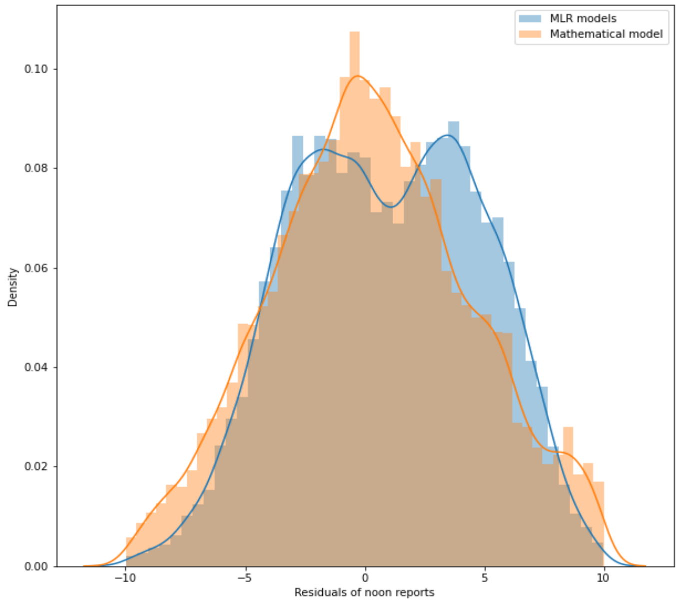

Figure 6: The density of the residuals in daily fuel consumption of the MLR models (blue) and the mathematical model (orange) for noon-reports.

predicted total consumption that is lower than 5% for both approaches. The distribution of errors in percentage is nearly comparable between both methods, although the mathematical model has more voyages with a percentage error close to 0%.

In our results, we presented the errors for the voyages and for the noon-reports of these voyages. The average MAE, RMSE, and MAPE errors calculated over all the noon-reports of each voyage in our dataset showed that the majority of voyages, on average, were well predicted (less than six MT/day and less than 20% errors). Then, for each point in our dataset representing a noon-report, we presented the residuals between the actual and predicted values, giving a distribution of errors between -10 and +10 MT/day with more noon-reports concentrated around 0 MT/day. Finally, for a standardized comparison between voyages, we presented the residuals between the total fuel consumption throughout each voyage and that predicted by the

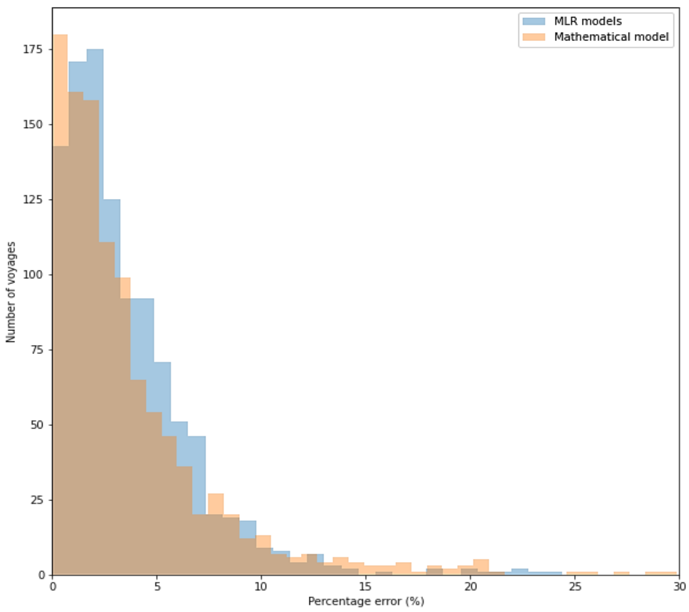

Figure 7: Density Distribution of Percentage Residuals in total fuel consumption for MLR Models (Blue) and Mathematical Model (Orange) in Voyages

models as a percentage, which showed that a large number of voyages have an error percentage lower than 5%.

Although the results of testing the models were similar for both approaches, the mathematical model performed better than the MLR models in terms of fuel consumption per noon-report and overall fuel consumption for each voyage. This proves first that the extension of the MLR model of [Hajli et al., 2023] was able to achieve good predictions for several categories of bulk carriers even when considering the average value of the meteorological factors on each noon-report. Secondly, an improvement of the results was observed in the case of the mathematical model since the latter considers all individual meteorological reports embedded in each noon-report and not an average value in addition to the constraint imposed on the total fuel consumption per voyage.

Furthermore, the fuel consumption of a ship have a significant impact on its emissions. In fact, the amount of fuel consumed has a direct influence on the amount of emissions produced by the ship according to the following equation presented by [Trozzi, 2010]:

$$E_{Trip,i,j,m} = \sum_p (FC_{j,m,p} \times EF_{i,j,m,p}) \quad (7)$$

In this equation, the emission over a complete trip ($E_{Trip,i,j,m}$) for a given pollutant (*i*), engine type (*j*), fuel type (*m*), and phase of the trip (*p*) is determined based on the fuel consumption ($FC_{j,m,p}$) and the emission factor ($EF_{i,j,m,p}$)

Integrating the proposed models into a vessel routing decision system would indeed improve voyage planning and reduce voyage costs by taking into account fuel consumption and emission levels under different weather conditions.

4 CONCLUSION

Maritime shipping is a sector that presents many challenges due to the number of the involved actors and the complexity of the operations that are interconnected. The environmental side adds to these challenges and requires more attention in view of the new IMO regulations and the targets it has set.

Controlling fuel consumption is one of the important keys to reducing emissions from this sector. The present study proposed two approaches for the prediction of fuel consumption for bulk carriers. In both approaches, meteorological conditions were added as an important factor affecting the performance and the energy efficiency of ships during sailing. We first proposed an extension of a model, which only concerns sister-ships, to other bulk carriers with different physical characteristics and thus different behavior during voyages. Our second proposal addressed the same problem while taking into consideration the different timing frequencies of noon-reports and weather reports in addition to the total fuel consumption on each voyage. The training and testing were performed on a large dataset, which allowed a better learning of the variations of the fuel consumption under different meteorological conditions.

Our study was able to accurately predict fuel consumption for the majority of voyages using an MLR model for each category of bulk carriers, and then further improved the predictions with a mathematical model, providing a single fuel consumption approximation for all categories in our dataset. However, further improvement is possible by including additional voyage information (Loading information, hull resistance, maintenance ...) into the models. Additionally, the quality of the acquired data has a significant impact on the modeling process, thus increasing data quality and diversifying data sources can improve the predictions. Furthermore, our models were trained on a limited number of vessel categories due to the limited variety of ships in our dataset. Therefore, models that can be applied to a wider range of vessels could be developed by incorporating a greater diversity of vessel types in the training dataset.

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