A data-driven approach for prediction and optimization of ship fuel consumption

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The continuous increase in annual greenhouse gas emissions pressures all industrial sectors to reduce emissions, move to green technologies, and become more efficient. In the shipping industry, there are several projects and technologies for reducing emissions by ships, both at the design and operation levels. One possible solution for existing ships is the installation of fuel optimization systems that automatically adjust engine rotations and propeller pitch to increase the propulsive efficiency of the ship. These systems optimize the fuel consumption in the route as a function of a set of variables such as speed, propulsive system parameters, and environmental conditions, which are monitored continuously throughout the voyages.

The objective of this dissertation is to develop machine learning models that represent the operation of a fuel optimization system and to develop a prototype of a decision support system that provides predictions of the optimal fuel consumption of the ship's main engine. For this purpose, a one-year sample of data collected from a ship's automated fuel optimization system is used, which includes the propulsion system parameters, environmental conditions, and fuel consumption of the ship in operation. This dataset is first analysed and pre-processed and then used in learning tasks with Artificial Neural Network and Support Vector Machines algorithms. The performance of the algorithms is assessed and then a two-stage model is developed to predict the speed and fuel consumption of the ship under operating conditions. Finally, the developed models are used in a decision support system that is developed and demonstrated in different operational scenarios.

Keywords: fuel consumption, fuel optimization, machine learning, artificial neural network, support vector machine, decision support system

1 INTRODUCTION

Despite the shipping industry being one of the most efficient modes of transport, it produces around 3% of the global greenhouse gas (GHG) emissions [1] and according to International Energy Agency (IEA) is a hard-to-abate industry [2], due to the difficulties in electrification, long lifespan of the fleet and high dependency of the fossil fuels.

Since 2011, IMO has published two studies [1], [3], about the impact of the shipping industry in the atmosphere regarding GHG emissions. The last one, published in 2020, showed that despite the carbon intensity indicator having decreased by 31%, the total CO_2 emissions have reduced only about 8%. This occurred due to the increase in the global economy and with that, the maritime transportation, and ships construction [1], also, the actual tendency is for the world fleet to increase by 6.3% until 2026 according to a recent report from BIMCO [4].

The MEPC in 2018 [5], was approved the IMO Decarbonisation Strategy, where the focus is to reduce the carbon intensity by 40% in 2030, compared with the 2008 base, reducing this index to 70% in 2050 with a total GHG reduction of all world fleet in 50%. Although there are several criticisms by politicians and countries about the numbers involved, this is the first time an entire industry has agreed to be more efficient and reduce the impact on the global environment.

To achieve these challenging goals, there are six major group measures with high potential of GHG mitigation, according to Bouman et al. [6]. One of them is the Weather Routing and Logistic Scheduling. It consists of studying the operation of the ship or fleet to find the best logistics, where one can find an optimum speed to a pre-determined ship configuration, combined with the weather prediction along the route. This allows the shipowner to meet port demand on time and minimize fuel consumption per cargo per mile during the voyage.

Another important group is about the Operational Speed of the Vessel and its relationship with its design speed. Conventionally, the ships are designed to operate at their hydrodynamic boundary speed. However, the required power is proportional to the product of speed and resistance, and the hull resistance curve starts to rise exponentially as the speed increases. Therefore, a reduction in operating speed causes a reduction in fuel consumption per cargo per mile.

Focusing on that groups, one of the improvements that can be used by shipowners in existing ships, is to install a fuel optimization system that automatically adjusts engine rotations and propeller pitch to increase the propulsive efficiency of the ship. These systems optimize the fuel consumption in the route as a function of a set of variables such as speed, propulsive system parameters, and environmental conditions, which are monitored continuously throughout the voyages. The data can be used not only to calculate fuel consumption but also, to identify points of improvement, such as operational bottlenecks, preventive maintenance or situations that hamper the ship efficiency improvement.

This is a challenge with the growth of ship automation, as larger datasets are generated that cannot be fully analysed by experts without proper numerical tools. So, automated processes with Artificial Intelligence (AI) and Machine Learning (ML) models have been used to help analyse these large datasets and to develop decision support tools [7]. The correlations between the data collected should be studied to use in the ML method. Also, pre-processing should be made in the data if necessary, and outliers and redundant variables should be removed so that the models can be more reliable. In addition, there are several ML methods, which should be studied and tested to assess which one can meet and predict the expected results. Each ship has its size, equipment, route, and own operation, so a model that fits each ship configuration must be found since there is no general model that can be used for all ships.

To try to correctly predict the fuel consumption and avoid errors due to the uncertainties present in the operational routine, some studies have been developed in the so-called black-box model, when the model is driven only by data and statistical methods, like the use of ship dataset and machine learning.

Pederson et al. [8] were pioneers to investigate the use of ANN to predict ship resistance based on the full-scale measurements of ship speed, wind speed and direction, sea and air temperature, in different load conditions. Also, they compared the results with the empirical and data-driven methods based on hydrodynamics relationships (e.g., Holtrop and Mennen) and concluded that the use of ANN is a better model to use in predicting operating resistance with differences ranging from 5 to 20 percentage points compared to theoretical models.

Farag et al. [9] studied an ANN prediction model for an oil tanker with a route between Sultan Qaboos Port, in Oman, and Rotterdam, in the Netherlands. The authors studied the correlation of 11 variables, related to wave, wind, current and ship speed, with the fuel consumption and modelling an ANN using a feed-forward neural network with the polynomial regression model in the hypotheses function. The results presented show a good prediction model with R^2 around 0.98. The authors also used the same route studied as an example of how to predict the fuel consumption before starting to navigate and how to study a just-in-time (JIT) scenario using the model.

A deep feed-forward neural network (DFN) was developed by Lazakis et al. [10], where the authors developed a process to use the ocean environmental data, like wave period, wave height, wind speed and angle, and water temperature, and the ship configuration as draught, speed over ground and heading, to develop and analyse the loss of the cost function of a fuel prediction model. They developed 540 models using DFN to find which has better results, changing the hyperparameters as the number of hidden layers, the number of neurons in hidden layers, the learning rate, the gradient optimizer, and the dropout parameter, this last one was used to prevent overfitting. The final model has an error of 3.5% compared to the test data.

Despite ANN being one of the most used models in FOC prediction, it is not always the best prediction model to be used, even if it can be scaled into a deep learning method, and with that find patterns, those other methods cannot. In Gkerekos et al. [11], a large comparison study was conducted to either compare two databases, noon reports and automated data, and different learning methods, e.g., Support Vector Machines (SVM), Artificial Neural Network (ANN), Random Forest Regressors (RFRs), among others. Using the features as main engine RPM, ship speed, wind speed and direction, sea state and direction, and draught, and changing the hyperparameters for each training model, a large analysis was done, analysing the convergence of each model, and comparing the best results. All models reached good prediction results of the testing dataset, with a coefficient of determination greater than 0.85, with the SVM being the best result with 0.91.

A support vector regression (SVR) model was developed by Kim et al. [12] for a 200,000-ton cargo bulk carrier, the objective, in addition to developing the main engine power prediction model, was to compare the machine learning method to the method presented in ISO 15016. The result showed that the model predicted from the data collected directly from the ship are more reliable than those derived from ISO 15016 for that specific vessel. The model presented a good prediction with a coefficient of determination about 0.89, better than the model presented by the ISO that resulted in 0.3. This difference occurred, according to the authors, because the ISO model assumes static sea conditions, and this is more evident when compared with the ML model for cases with the severe sea.

2 CASE STUDY

An automated optimization system has been installed on a container ship with 126 m length of a Portuguese shipowner. The system is intended to reduce the impacts caused by environmental conditions during navigation, controlling the maximum fuel consumption. The automated optimization system can adapt the shaft rotation, the pitch angle of the propeller and the fuel rack position of the main engine to ensure that the fuel consumption does not exceed the set value, according to the inputs from the environment and fuel consumption and shaft thrust meter. The system monitors various subsystems, all correlated with fuel consumption and energy spending. The list of variables recorded by the automated system is detailed below.

- Time: The exact time of record, with seconds, minutes, hours, day, month, and year.
- Latitude and Longitude: in degrees.
- Speed Over Ground in knots.
- Apparent Wind Angle in degrees.
- Apparent Wind Speed in [m/s].
- Total Fuel Consumption of the ship in [t/24h]
- Total Propulsion Consumption in [t/24h].
- Total Propulsion Power in [kW].
- Total Shaft Generator Power in [kW].
- Total Main Engine Power in [kW].
- Main engine rotation per minute.
- Total Auxiliary Engine Power in [kW].
- Total Auxiliary Engine Consumption in [t/24h].
- Propeller rotation per minute.
- Propeller pitch angle.
- Fuel temperature in [°C].
- System fuel optimization (ON, OFF): Feature that provides the information if the automated system is on or off using the Booleans numbers, as 0 when it is OFF and 1 if it is on.
- Fuel consumption set: Indicator showing the maximum fuel consumption to be optimised by the system in [t/24h].

To have a reduced database, to facilitate the verification of correlations, reduce the size of computational memory usage and the computational calculation time, a redundancy analysis of the variables is carried out to verify which of them could be removed. Also, a data division is applied based on the distribution, having the speed of 10 [knots] as a cut-off value, to remove the datasets where the ship is whether in manoeuvring to proceed towards or departs to the port or she is at the pier loading and unloading operation.

After splitting the database to use only navigation with a speed above 10 knots, some treatments and adjustments are applied to the features to be able to verify the correlations between them, their consistencies and to analyse their behaviour.

The heading of the ship is needed to calculate the true wind angle also, it is an input of the learning model as it is correlated with the influence of the wave and wind in the ship resistance. As the instantaneous values of the ship heading are not available in the dataset, it is approximated by the bearing angle between two consecutive coordinates (i.e., latitude and longitude) recorded during the routes.

The forward and aft draught are recorded not in an automated way. They are given from the initial route reports when the ship is departing from a port. So, it is calculated the mean draught and trim, as in [13].

The wind measured in the ship is the apparent wind speed (AWS) and apparent wind angle (AWA), but the true wind needs to be calculated to correct develop the prediction model because, as the operator does not know the future speed of the ship, the wind used as input data for the prediction model must be the true wind, with speed and angle, in the route region

The wave is one of the main factors contributing to the increase in the ship's resistance [14] and in consequence of that, the fuel consumption. To add these features the Copernicus Climate Data Store [15] is used, from this data store, it is obtained the "Mean Wave Period", the "Significant height of combined wind waves and swells" and the "Mean wave direction", to all the area and time of the ship´s route recorded.

For the original dataset with 25019 records, only 11597 have the velocity equal to or above 10 [knots]. Also, it is verified that in one route the draught configuration and trim values were missing and this dataset, along with all variables related to that specific time, have been removed from the dataset to guarantee the reliability of the results, since it is not guaranteed that all the learning models and scripts can handle with missing values. Table 1 summarises the dataset final characteristics.

Table 1. Dataset cleaning summary

Dataset	Number of cases
Full database	25019
Equal or above 10 [knots]	11597
Less than 10 [knots]	13422
Missing datasets	258
Outliers	302
Final database	11116

3 DATA ANALYSIS

After splitting the databases, applying filters, and transforming and including other variables a Spearman rank-order correlation is applied to verify the correlation between each variable. That method was applied in [16] and [17] and helped the authors to find the characteristics that have the highest correlation, as this is not easy to visualise due to the non-linearity between the variables.

Figure 4 shows the relationship between the ship's operating conditions, with its draught, trim and fuel consumption set. The trim and draught have little influence on speed and fuel consumption, something also not expected, as seen in some studies [11], [18]. This occurs because draft and trim are not varying with time, i.e., the variables are static throughout the route period, so this correlation fails to capture the influence of the two variables on speed and fuel consumption Also, the environmental conditions appear to not affect either the speed of the fuel consumption.

This occurs due to the automated optimization system installed in the ship where the system has a full correlation with the fuel consumption as one can see in Figure 1, where it can be seen that the propulsion consumption is almost the same as it is set in the system, in other words, the propulsion system always operates within the limit imposed by the system operator.

It is difficult to develop a model to predict the fuel consumption with this high correlation between the actual fuel consumption and the set fuel consumption, in addition, there is a high usage rate of the system, which is about 98% of the time travelled. This means that the ship will always operate at the system limit so there is no way to predict the fuel consumption as this will be whatever the system operator sets. The model then needs to be made to study whether it is possible to achieve a speed with given fuel consumption.

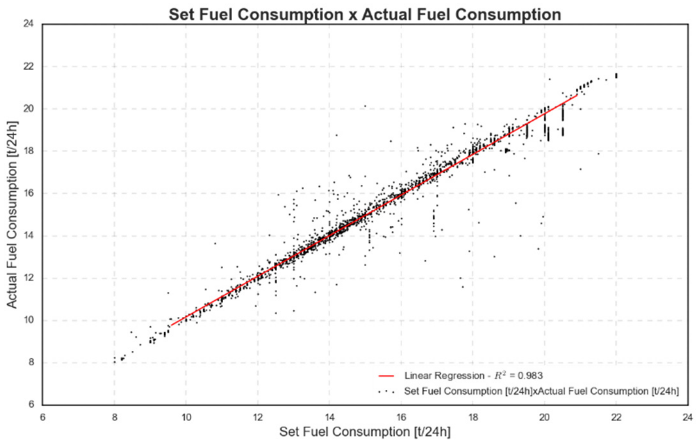

Figure 1. FOC – settled versus actual fuel consumption

Two of the propulsion subsystems influenced by the automated system are the propeller pitch and the shaft rotation speed. One can verify the scatter plot of them with the main engine power in Figure 2 and Figure 3, where on the propeller pitch graph is clear to see that there are some distinct operating patterns.

Also, on the shaft rotation speed graph, a clear straight line can be seen as the upper limit between the relationship between the shaft rotation speed and propulsion power, the same occurs at the lower limit of shaft speed, around 119 RPM. This represents the engine's minimum rotation point.

There is a clear distinct operating condition where either the propulsion system works at the operational limits of the ship's shaft with the engine rotation, or in an operational situation where the rotation is around 150 RPM. But in the latter case without any apparent pattern of operational limit condition nor high correlation behaviour.

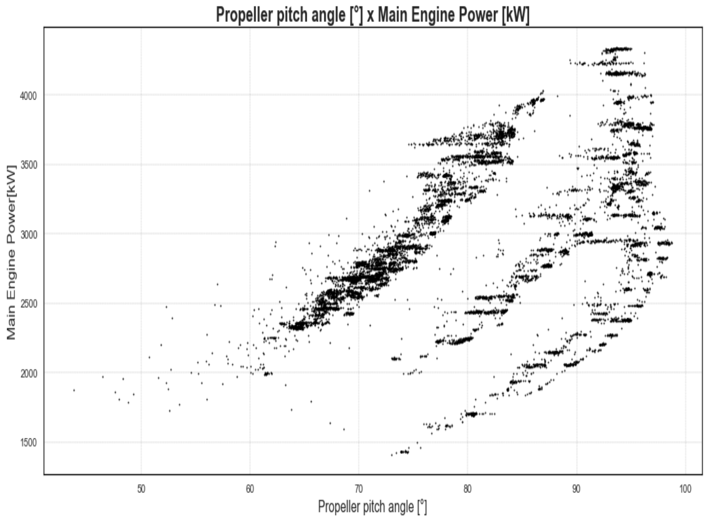

Figure 2. Propeller pitch angle x Total Propulsion Power

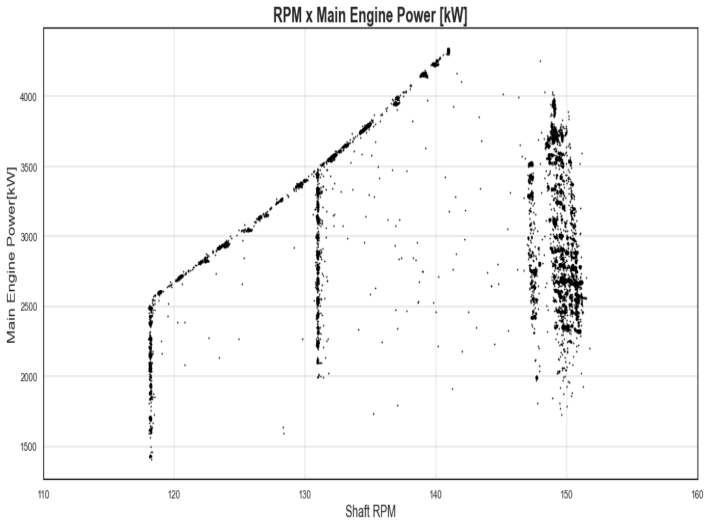

Figure 3. Shaft rotation speed x Total Propulsion Power

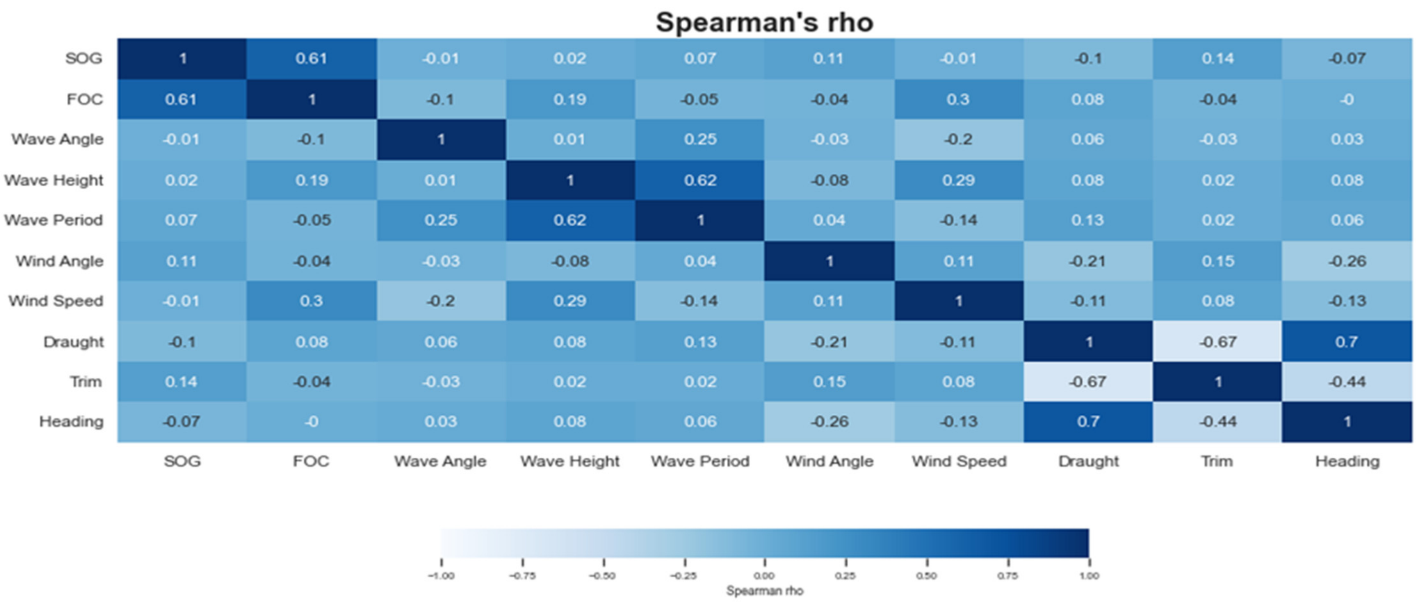

Figure 4. Spearman's rho analysis between SOG and FOC with operational conditions

4 FUEL CONSUMPTION PREDICTION MODEL

To develop a machine learning model for fuel consumption analysis, a predictive model with the variables representing the propulsion system is proposed. These variables have as a characteristic the direct influence of the automated optimization system. This is a way to use as an input the automated system, without using the "set maximum fuel consumption" variable since it has a high bias. If this variable is used as input, whatever the value of this variable, a remarkably close value will be the result of the prediction model, in the same way as the data presented in Figure 1.

A two-stage model is proposed to solve this high influence problem. The first stage is developed to study and get a reliable prediction method for the speed over ground from a ship's configuration and weather conditions. The second-stage model is aimed to find an ML model to predict the fuel consumption for the propulsion system.

The objective of the two-stage model is to verify in the first stage if a given SOG, for a given weather condition and ship configuration, is feasible and under what operating conditions, i.e., shaft rotation speed, propeller pitch angle and fuel rack position. The corresponding operating conditions are then used in the second stage to predict the propulsion fuel consumption, as shown in Figure 5.

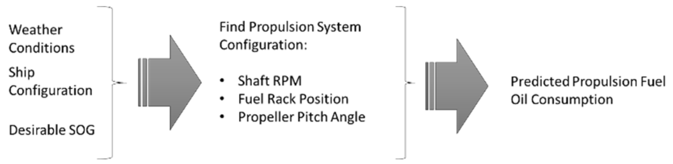

Figure 5. Schematic of the two-stage model

4.1 *First Stage*

A machine learning first stage prediction model is developed using the features of the weather conditions, i.e., wave and wind, for each position of the studied routes; the ship configuration, i.e., draught, and trim and the propulsion configuration as fuel rack position, shaft rotation speed and propeller pitch angle.

The first method used is the Artificial Neural Network (ANN). The combination of hyperparameters presented in Table 2 was tested to find a better convergence to this particular solution. The λ value is the regularization term that penalizes the cost weights in the cost function, which is used to avoid overfitting. The number of hidden layers and their nodes is modified to analyse how deep need to be this neural network to achieve a good prediction. Also, the solver Adam [19] is used to optimize the weight calculations and it is assessed which activation function provides the best result, evaluating the hyperbolic tangent, the ReLU and the identity functions.

Table 2. Hyperparameters of ANN model

Hyperparameter	Values/Type of function
Regularization Term - λ	$\in [0,1.28]$
Number of hidden layers	$[1,2,3]$
Number of nodes	$\in [2,100]$
Solver	Adam
Activation function	Tanh, ReLU, identity

Table 3 presents the results for each size of the neural network. One can see that with the growth of the network the performance of the model increases. Also, the regularization term is low, which means that the weights applied to the variables are not causing overfitting. Still, the activation function as a hyperbolic tangent is expected since in similar studies [11], [20] it had a better performance compared to the others.

Table 3. ANN results to speed prediction

Size of ANN	Number of Nodes	Regularization Term - λ	Activation	Score - R^2
1 hidden layer	(100)	1.28	tanh	0.8128
2 hidden layers	(100,80)	5e-3	tanh	0.8567
3 hidden layers	(200, 100, 80)	1e-5	tanh	0.8887

To test and compare with other machine learning methods and to try to improve the score, a Support Vector Machine (SVM) model is developed, as it has been successfully implemented in some fuel prediction studies as already mentioned. In Table 4 one can see the hyperparameters that are used to analyse and find a good configuration for the prediction model.

Table 4. Hyperparameters of SVM model

Hyperparameter	Value
Gamma	$\in [2^{-15}, 2^0]$
C – Regularization parameter	$\in [2^0, 2^8]$
Epsilon	$\in [10^{-4}, 1]$
Kernel	Radial Basis Function

The same dataset used in the ANN model is used by the SVM model, with the training and test data split, also. A script in Python is developed to calculate the prediction model of each set of hyperparameters configuration and each score using the Scikit-learn library already mentioned, using the Epsilon-Support Vector Regression[1] function to analyse the data. The best solution found is shown in Table 5 and the scatter plot of the results compared with the data is in Figure 6.

The model obtained has better accuracy than the ANN. Besides that, the regularization parameter did not extrapolate to the maximum that it could, that is, the

[1] https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVR.html

solution obtained avoided overfitting with high regularization parameters. The gamma value found is small and shows that the model found a solution where the kernel calculation does not vary smoothly, having minor variation, which could cause overfitting in some models.

Table 5. SVM results to speed prediction

Hyperparameter	Value
Gamma	4.00e-04
C – Regularization parameter	32
Epsilon	1.42e-01
Score (R^2)	0.9256

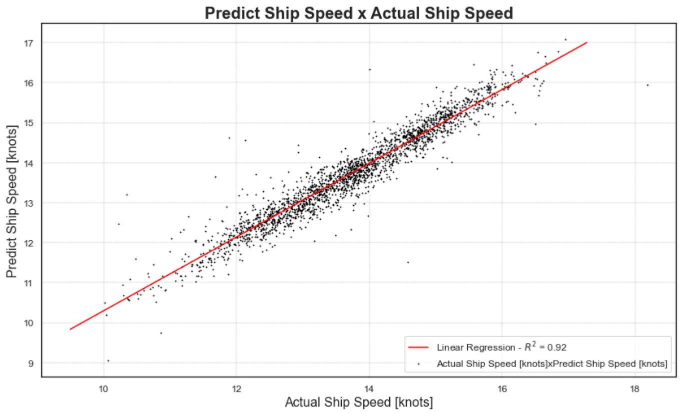

Figure 6. Scatter plot result of the predicted and actual value - SOG

4.2 *Second Stage*

A second stage model is developed to generate fuel consumption predictions for the propulsive system. It is proposed that this model is trained to receive the data resulting from the first stage model and thus indicate what the consumption would be for a given route and expected speed.

Also, the same hyperparameters are used in both machine learning models, ANN as in Table 2 and SVM as in Table 4.

The results of the ANN model are shown in Table 6. This model contains the input data with more correlation between them so that the simpler neural network system already showed satisfactory results, with $R^2 \approx 0.98$, very similar to those presented with more hidden layers.

Table 6. ANN results to fuel consumption prediction

Size of ANN	Number of Nodes	Regularization Term - λ	Activation	Score - R^2
1 hidden layer	(100)	1.0e-4	tanh	0.979
2 hidden layers	(100,100)	0.002	tanh	0.988
3 hidden layers	(200, 100, 40)	0.01	tanh	0.989

For the SVM model, the same hyperparameters shown in Table 4 are used, and the same inputs are used in the ANN model, with the same training set and test set. The best result found can be seen in Table 7. The model results fit the observed data very closely, as shown in Figure 7.

Table 7. SVM results to fuel consumption prediction

Hyperparameter	Value
Gamma	1.10e-04
C – Regularization parameter	256
Epsilon	1.00e-04
Score (R^2)	0. 9971

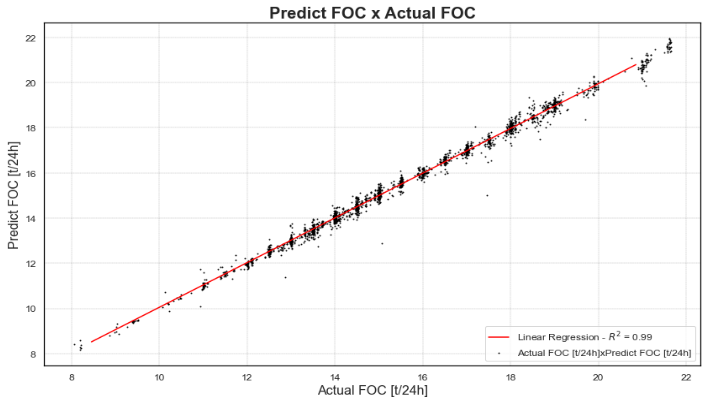

Figure 7. Scatter plot result of the predicted and actual value – FOC

4.3 *Two-stage model results and predictions*

The models chosen for the solution are for the first stage, the SVM with the hyperparameters of Table 5 and the second stage, the SVM model with the hyperparameters of Table 7, since they both have a good prediction score.

With the two-stage models already defined, a script is developed so that the first stage model is an input for the second stage model, as outlined in Figure 9. Thus, the two-stage model proposed can analyse each set of propulsive systems, predicting the speed and consequently analysing the consumption of the chosen system. Figure 8 shows the results predicted by the model compared to the real observed consumption. The model has a good adherence, with a coefficient of determination of around 0.99.

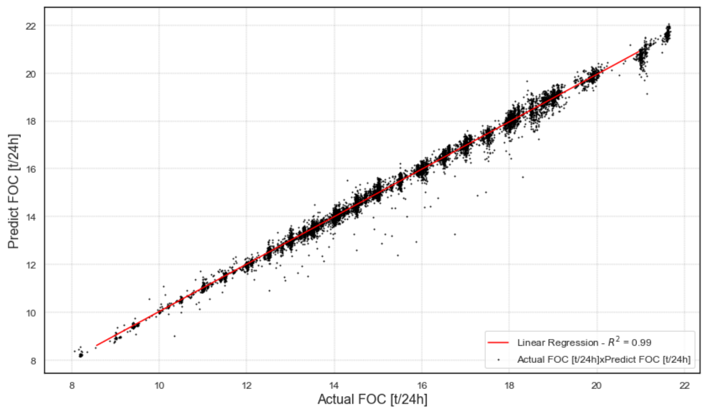

Figure 8. Scatter plot of predicted and observed FOC values – Two-stage model

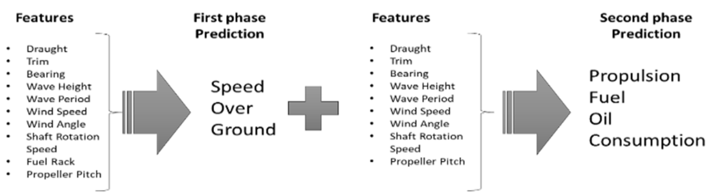

Figure 9. Two-stage fuel consumption prediction model

5 DECISION SUPPORT SYSTEM

A decision model was developed to exemplify how the developed ML models can be used. Figure 10 shows the schematic design of the code developed in Python for this analysis.

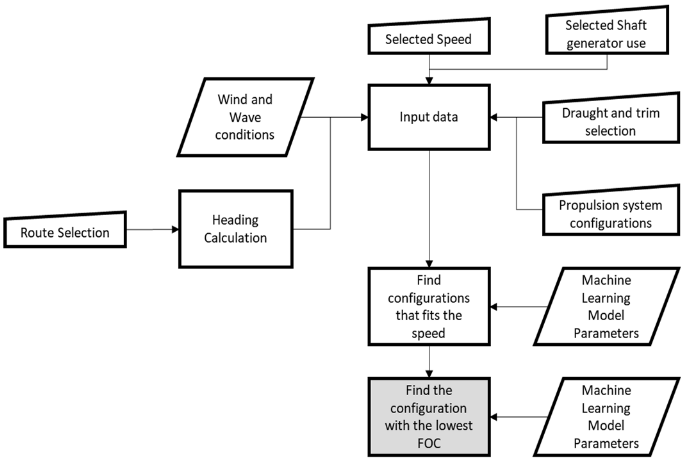

Figure 10. Decision Support System

The first step of the model is to build the dataset to be analysed. The parameters to be inserted are the route to be navigated, the speeds to be analysed, the use or not of the shaft generator and the draft and trim conditions of the ship. With these data, the program should actively or passively add the environmental data and calculate the ship's heading based on the route. Thus, assembling the dataset of the route to be investigated.

Thus, in the second step, the model verifies for each position of the route with each configuration of the propulsion system, if it reaches a speed greater or equal to the requested speed. The predicted fuel consumption, the third step, is calculated for each configuration that achieves the desired speed, thus knowing which is the lowest fuel consumption for that minimum speed.

An analysis is done to compare the prediction for different speeds (Figure 11), without the use of the shaft generator. As expected for higher speeds there is higher fuel consumption, where one can see the fuel rack followed the same behaviour of the FOC. The shaft rotation at the speeds of 12 and 14 knots is low and increases for the speed of 16 knots to compensate for the limitations of the propeller pitch angle, which was already close to the limit at the speed of 14 knots. Thus, for the 16 knots case, the model increased the shaft rotation to obtain more thrust in the propulsion system. Further analysis is needed to understand why the model prefers to use 119 rpm rather than 130 rpm, and whether it represents the ship's current propulsion system.

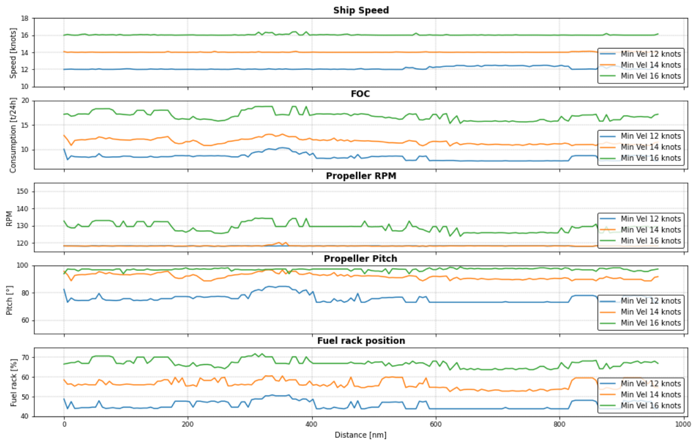

Figure 11. DSS result for different speeds without the use of shaft generator

To perform a sensitivity analysis of how the model behaves with some variables, an analysis was made simulating a calm water condition. With these environmental conditions, the cases from 12 to 16 knots were simulated, with the results shown in Figure 12, where it shows the results for the total fuel consumption for the entire route for each ship's speed. One can see that the model understood the relationship between speed and consumption as a polynomial function relationship, as expected.

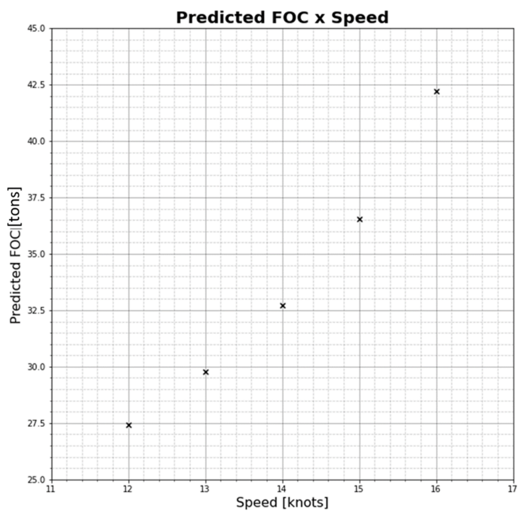

Figure 12.Predicted FOC based on different Ship speed

Similar to the previous simulation, a new analysis was done, but in this case, varying the significant wave height. The wind condition remained the same, with the wind at 4 [m/s], the ship's speed was chosen as 13.5 knots, and the analysed wave conditions vary from 1.0 [m] to 3.5 [m] of significant wave height. In Figure 13 the results show a practically linear increment with the increase of the significant wave height.

Also, was performed the sensitivity analysis using different wind speeds and draughts. As in Figure 14 and Figure 15.

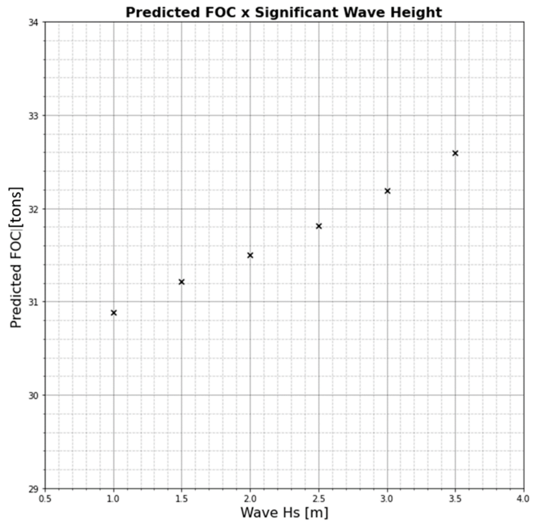

Figure 13. Predicted FOC based on different Significant Wave Height

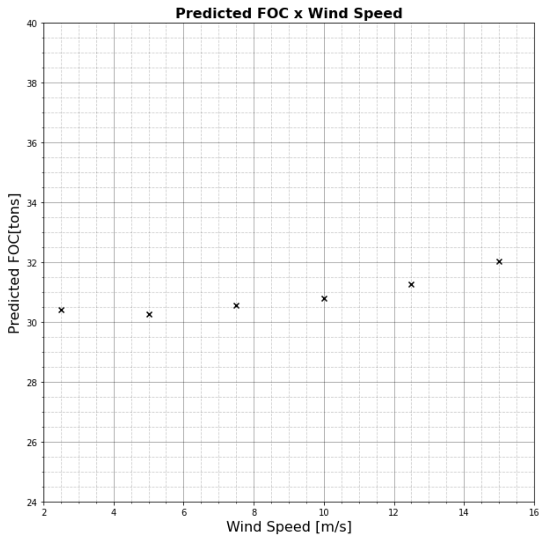

Figure 14. Predicted FOC based on different Wind Speed

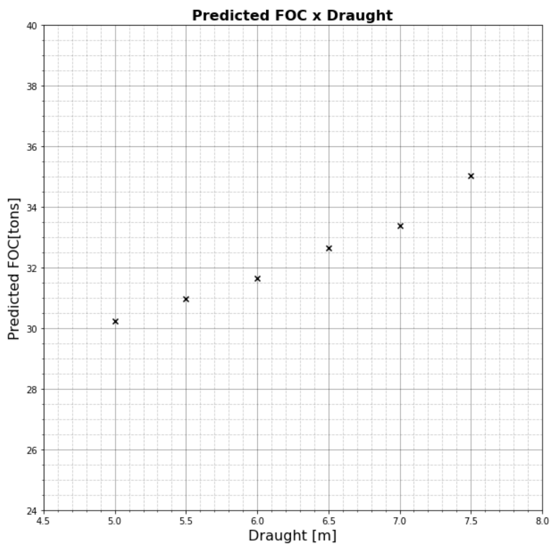

Figure 15. Predicted FOC for different ship's draughts

These analyses serve the purpose of understanding how the machine learning models perceived the influence of each variable related to this ship under specific operational conditions. The model identified a large influence of the ship's speed and draught, as already expected. However, the significant wave height and wind speed have a low impact on the FOC predictions.

6 CONCLUSION AND FUTURE WORK

6.1 *Conclusion*

This dissertation has developed machine learning models that represent the operation of a fuel optimization system and has developed a prototype of a decision support system that provides predictions of the optimal fuel consumption of the ship's main engine.

The study was developed based on a one-year sample of data collected from a ship's automated fuel optimization system, which includes the propulsion system parameters and fuel consumption of the ship in operation as well as data on the environmental conditions and other variables that were added to enrich the dataset.

The analyses performed on the dataset demonstrated that the automated system for fuel consumption optimization is reliable since the actual fuel consumption along the ship voyages is always very close to the set value. Moreover, by optimizing the propulsive system all the time to guarantee the set consumption, this system makes the environmental variables appear uncorrelated with the speed and with low impact with the fuel oil consumption.

This has affected the preliminary Machine Learning models proposed to predict the fuel consumption, because the variables used by the model present low correlation, making the final model not perform well.

A 2-stage Machine Learning prediction model was proposed using the features such as the shaft rotation speed, fuel rack and propeller pitch. In the first stage, Artificial Neural Network and Support Vector Machines models were developed to predict the ship's speed based on the ship configuration, weather conditions and propulsion system configuration, with the Support Vector Machines the method showing best prediction accuracy on the dataset, with a score of 0.92.

The second stage model was developed to predict the fuel consumption of the main engine also using Artificial Neural Network and Support Vector Machines models. In this case, both methods had a good performance, with scores of 0.99 and 0.98, respectively.

The proposed two-stage model proved to have good accuracy, reaching 0.99 in the score value when using the Support Vector Machines model in both stages, as it presented a better result in each stage.

The Decision Support System was proposed and formulated based on the 2-stage prediction model, to evaluate what would be the fuel consumption for a chosen minimum speed, using or not the shaft generator. The first stage assesses if the target speed is reached for a given operating condition, and in the second stage, the fuel consumption for each condition of the first stage is calculated. It is shown some examples of how to use the system and a sensibility analysis that provides indications of the influence of selected variables on the total ship's fuel consumption. It was shown the large influence of the ship's speed and draught, as already expected and the low impact of the environmental conditions. This reinforces the findings of Spearman's correlation analysis, where the correlation between the environmental conditions and the ship's speed and FOC are minimal.

The developed models need to be tested and adjusted for ship operation. New variables and larger datasets properly pre-processed may be required. It is suggested to collect more data or, if possible, to try to use the model to find out how adherent this model is with reality. New tests can be made including new variables such as engine speed and fuel temperature, as long as it is known how much the optimisation system influences these variables.

6.2 *Future work*

The 2-stage model has been shown to provide good predictions, as presented in Chapter 4.3. Even removing one of the variables, the system shows a good score of 0.99 in the FOC prediction. However, further studies should be carried out and compared to verify the validity of the use of these models in a DSS, since it is not clear that the machine learning method captures all the influences necessary to predict the FOC using this decision support system. Also, this model was developed with a focus on fuel consumption and not to find out the impact of each component that interferes in consumption. For that, a specific model must be created, with specific dataset treatments for each case under study, similar to what was done by Dinham-Peren et al. [21], in the study of ship resistance in calm water conditions using operational data.

The input in the DSS model can be complemented with theoretical models, creating a so-called grey model, combining the parametric models with the ML methods. There are a few studies in that area, as by Leifsson et al. [22] and Haranen et al. [23]. These models can prevent the system from choosing a set of solutions that would not be feasible for the ship's propulsion system to achieve a speed with the desired fuel consumption. Thus, avoiding a possible bias or overfitting of the prediction model.

The SVM model seemed to provide better results in this dataset, but in future work, after comparing with new real observations, it is necessary to verify if there is some kind of unbalance between the variables that may require a reanalysis and new treatments of the dataset, which could be subjected to standardization to achieve better results. Also, in future work, deeper ANNs could be tested, including non-linear relationships between the variables.

Analyses of new scenarios can be made, but these must be in accordance with the range of the model, because any prediction model has its limits in the range of the input data, and extrapolating values outside of this range may not correspond to reality.

In this study, it was not possible to access the types of sensors and their uncertainties. It is known that there are biases and uncertainties in the measurement instruments. The ISO 19030 - Ship Performance and Condition Monitoring [24] provides guidance and introduce good practices on that. Future work would be to analyse these uncertainties and implement them in the model to know the total uncertainties of the model. Some studies have analysed these uncertainties as by Hagestuen et al. [25], Thornhill et al. [26], Aldous et al. [27] and Aldous [28], but they have not coupled them to a machine learning prediction model.

Better models can be built with other Python libraries, like Keras [29]. This library contains more models and machine learning functionalities and possibilities to work with parallel computing, which would speed up the analysis process.

Several applications can be developed using this model as a starting point, in addition to the decision model for shipowners focusing on the speed analysis and fuel consumption by the main engine. It can be used to plan a route based on environmental and ship conditions, as for this it would be only necessary to have the environmental forecasts and the ship's operational condition. For this, a model based on the Dijkstra algorithm should be used, changing it to allow the software to consider not only the distance but also the consumption for each section analysed [30]

A just in time (JIT) tool can be constructed, as in Farag and Ölçer [9], to try to optimize the sailing time and the waiting time for port entry, thus being able to optimize the speed during the route and consuming less fuel, also making the ship not wait in a queue, reducing the consumption of more expensive fuels such as MDO. This tool could work integrated within the ship system.

The prediction model can also be used to check if the ship complies with regulatory standards, verifying if the carbon index is within the limits imposed for that class of ships. For example, using the EEOI, one can calculate the carbon index based on the total FOC of the routes.

A digital twin can be modelled, as in Coraddu et al. [31], to study how the ship would behave in new scenarios, equipment changes or marine fouling growing. This type of development involves larger datasets enriched with additional variables and a complete understanding of how they relate to each other.

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