ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

ΤΜΗΜΑ ΝΑΥΤΙΛΙΑΚΩΝ ΣΠΟΥΔΩΝ

ΠΡΟΓΡΑΜΜΑ ΜΕΤΑΠΤΥΧΙΑΚΩΝ ΣΠΟΥΔΩΝ

ΣΤΗΝ ΝΑΥΤΙΛΙΑΚΗ ΔΙΟΙΚΗΤΙΚΗ

FUEL CONSUMPTION STRATEGIES USING DIGITAL BUSINESS

Ασπασία -Στυλιανή Γιαλαμά -Χανιωτάκη

Διπλωματική Εργασία

που υποβλήθηκε στο Τμήμα Ναυτιλιακών Σπουδών του Πανεπιστημίου Πειραιώς ως μέρος των απαιτήσεων για την απόκτηση του Μεταπτυχιακού Διπλώματος Ειδίκευσης στην Ναυτιλιακή Διοικητική

Πειραιάς

Απρίλιος 2022

Το άτομο το οποίο εκπονεί την Διπλωματική Εργασία φέρει ολόκληρη την ευθύνη προσδιορισμού της δίκαιης χρήσης του υλικού, η οποία ορίζεται στην βάση των εξής παραγόντων: του σκοπού και χαρακτήρα της χρήσης (εμπορικός, μη κερδοσκοπικός ή εκπαιδευτικός), της φύσης του υλικού, που χρησιμοποιεί (τμήμα του κειμένου, πίνακες, σχήματα, εικόνες ή χάρτες), του ποσοστού και της σημαντικότητας του τμήματος, που χρησιμοποιεί σε σχέση με το όλο κείμενο υπό copyright, και των πιθανών συνεπειών της χρήσης αυτής στην αγορά ή στη γενικότερη αξία του υπό copyright κειμένου.

Η παρούσα Διπλωματική Εργασία εγκρίθηκε ομόφωνα από την Τριμελή Εξεταστική Επιτροπή που ορίσθηκε από τη ΓΣΕΣ του Τμήματος Ναυτιλιακών Σπουδών Πανεπιστημίου Πειραιώς σύμφωνα με τον Κανονισμό Λειτουργίας του Προγράμματος Μεταπτυχιακών Σπουδών στην Ναυτιλιακή Διοικητική.

Τα μέλη της Επιτροπής ήταν:

- Dr. Ιωάννης Λαγούδης (Επιβλέπων)

- Ιωάννης Θεοτοκάς

- Διονύσης Πολέμης

Η έγκριση της Διπλωματική Εργασίας από το Τμήμα Ναυτιλιακών Σπουδών του Πανεπιστημίου Πειραιώς δεν υποδηλώνει αποδοχή των γνωμών του συγγραφέα.»

ACKNOWLEDGMENTS

This study is part of a master's thesis for the Master of Science in Shipping Management degree at the University of Piraeus. The study will last four months, beginning in January 2022 and ending in April 2022.

First, I would like to warmly thank Mr. Stavros Meidanis for the trust he has shown me in entrusting me with this dissertation and the opportunity he has given me to deal with such an interesting and topical issue.

Special thanks also to the supervisor of this research, Dr. Ioannis Lagoudis for the valuable scientific assistance provided to me throughout the writing process. Both his thorough scientific training and his ethos and kindness contributed significantly to the completion of this work.

Next, I would like to warmly thank the shipping company X and all the friends, colleagues, and associates of the Group for the advice and scientific guidance they offered me in order to complete the writing of this dissertation. Their knowledge, experience, and key tips have given them invaluable help in achieving a goal based on a solid theoretical background, framed by the experience that comes from the real field of operation of a ship. I would also like to express my special thanks to Mr. Dimitrios Panou, First Engineer, for the love and patience he showed me in my first contact with the Shipping sector, opening new paths full of knowledge and experiences.

Finally, I would like to express my deep gratitude to my family for their moral support, tolerance, and full support, without pressure or demands. The completion of this effort would not have been possible without their own deprivations all the previous years and I thank them warmly for that.

ABSTRACT

Optimizing ship performance is today an urgent need both to reduce fleet operating costs and to reduce greenhouse gas emissions. The purpose of this thesis is to examine how weather conditions can affect fuel consumption on ships and to what extent. More precisely, the aim of the present study is to investigate the correlations between the various factors affecting the energy efficiency of ships, both through the description of the theoretical background and through a practical analysis of a set of data derived from the actual operation of a fleet of two tankers. Such an analysis can be incorporated into the energy management systems of businesses with ships of a similar size, as it can assist ship operators in determining the best course of action for enhancing the vessel's operational performance and fuel efficiency while also lowering emissions of pollutants, which will lower operating costs for the shipping company.

ΠΕΡΙΛΗΨΗ

Η βελτιστοποίηση της απόδοσης του πλοίου είναι σήμερα μια επείγουσα ανάγκη τόσο για τη μείωση του λειτουργικού κόστους του στόλου όσο και για τη μείωση των εκπομπών αερίων του θερμοκηπίου. Σκοπός της παρούσας διπλωματικής εργασίας είναι να εξετάσει πώς οι καιρικές συνθήκες μπορούν να επηρεάσουν την κατανάλωση καυσίμου στα πλοία και σε ποιο βαθμό. Πιο συγκεκριμένα, στόχος της παρούσας μελέτης είναι να διερευνήσει τις συσχετίσεις μεταξύ των διαφόρων παραγόντων που επηρεάζουν την ενεργειακή απόδοση των πλοίων, τόσο μέσω της περιγραφής του θεωρητικού υποβάθρου όσο και μέσω μιας πρακτικής ανάλυσης ενός συνόλου δεδομένων που προέρχονται από την πραγματική λειτουργία ενός στόλο δύο δεξαμενόπλοιων. Μια τέτοια ανάλυση μπορεί να ενσωματωθεί στο σύστημα διαχείρισης ενέργειας εταιρειών με παρόμοια πλοία, καθώς μπορεί να βοηθήσει τους φορείς εκμετάλλευσης πλοίων στην επιλογή των πιο αποτελεσματικών μέτρων προκειμένου όχι μόνο να επιτύχουν την απόδοση καυσίμου και τη διαρκή λειτουργική απόδοση του σκάφους αλλά και να μειώσουν τις εκπομπές ρύπων, γεγονός που θα οδηγήσει επίσης σε χαμηλότερο λειτουργικό κόστος για τη ναυτιλιακή εταιρεία.

Keywords: Shipping, Big data, Fuel consumption, Energy efficiency

To Mother Mary,

I hope you do not hurt up there anymore.

You will be our Angel forever.

CONTENTS

LIST OF FIGURES AND TABLES

1. INTRODUCTION

1.1OBJECT-PURPOSE

The purpose of this work is the study of the factors that affect the fuel consumption of a ship during its operation, composing the information provided by the literature, as a theoretical background, the experience of the seafarers in the field of Shipping, but also the practical analysis of a set of data derived from the actual operation of a fleet of two tanker ships. The aim of this work is to highlight the importance and expected benefits of analyzing large-scale data on a ship's energy performance, the challenges it faces, and the possibilities that machine learning applications can offer in the context of sustainable development in the field of Shipping. The contribution of controlling the energy efficiency of a ship is manifold: initially, monitoring fuel consumption can yield significant economic benefits, which help reduce the operating costs of the management company and at the same time increase the competitiveness of its fleet. In addition, it helps to improve the operation of the ship, by ensuring the optimal operation of its machinery and its safe navigation through the most appropriate route, considering various parameters that affect fuel consumption, such as weather conditions and sea currents. At the same time, reducing fuel consumption reduces greenhouse gas emissions and other pollutant emissions, thus protecting the environment. The contribution of the present work lies in the fact that it is a brief - but complete - guide to the factors that affect the fuel consumption of ships, starting from the theoretical background and ending with the analysis of data from the "real world". Utilizing the experience of Shipping experts, the opportunity was given to bridge the theory with the practice, to highlight the benefits and the challenges that one must face when analyzing large-scale data on fuel consumption in ships. Especially today, when climate change control is a priority for all mankind and therefore the issue of energy consumption and the consequent production of greenhouse gases by ships is a dominant item on the agenda of current maritime policy, the optimization of its operation can deliver multiple economic, operational, and environmental benefits. Thus, the results of this dissertation are the basis for the analysis of the energy efficiency of ships and can be exploited with several extensions in the field of energy management research in the field of Shipping.

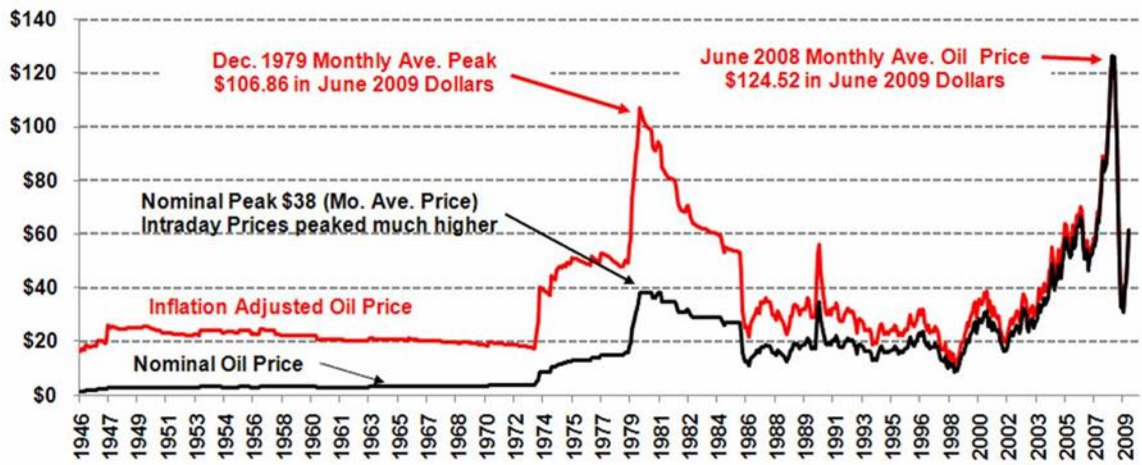
1.2 PROBLEM DEFINITION

The interest in controlling the energy efficiency of the ship is related to economic, environmental, and technical factors. The pursuit of a better understanding of a ship's operational performance is directly linked to fuel costs and environmental pollution. Several ship energy efficiency monitoring systems, business strategies, energy-saving systems, and research were developed in the 1980s following the oil recession in the late 1970s. Over the past 5 years, interest in saving and controlling energy has returned to the forefront due to high oil prices and the urgent need to take urgent action to tackle climate change.

1.2.1 Economic benefits

In the period of 1949-2009, there was an oil crisis in crude oil prices. This is due to high demand, reduced production, speculative phenomena, political instabilities. It has been observed that the cost of extraction is increasing while in 2002 4 times more oil was consumed than that found from new sources. This has a direct impact on the cost of fuel on ships which has reached 60% of their operating costs. For this reason, now shipowners are looking for the best ways of operating the ship from an energy point of view which is possible through the monitoring of fuel consumption.

Figure 1: Nominal and real oil price 1946-2009



Source: https://www.mordorintelligence.com/industry-reports/africa-offshore-support-vessels-market-industry

1.2.2. Environmental regulations

In April 2015, the regulation on maritime traffic "Monitoring, Reporting, Verification-MRV" for the monitoring of the emissions of carbon dioxide was approved. These days, every ship larger than 5000 dwt must implement carbon dioxide emission monitoring systems. Shipping companies must comply with the following:

1.By 31 August 2017 they had submitted to the auditors the plan by which they monitor ships over 5000 dwt on carbon dioxide emissions.

2.From January 1, 2018, should monitor and report data on consumption, distance, time in ports, and weather conditions to calculate the average of their energy efficiency.

On January 1, 2020, the IMO "sulfur cap" regulation came into force, which requires the percentage of sulfur to be reduced to 0.5% from 3.5%.

After 2020, the shipping community has begun to focus on the Paris climate goals. The IMO member states agreed in 2018 to reduce carbon dioxide emissions by 50% by 2050. So far, no reliable systems have been found that can comply with this agreement. Intermediate solutions to this goal are LNG and the use of biofuels. Alternatives could be the use of synthetic fuels, methanol, and Hydrogen but more research is needed to make them a technically and environmentally sustainable solution.

1.2.3 Marine fuel types and specifications

The international standard ISO 8217, which has been in effect since 2005, defines the required properties and specifications of diesel used in marine diesel engines. Ship fuels are classified as distillation (refining) fuels or residuals.

- Distillation fuels

This type of fuel is the most expensive on the market, and that is the reason that to this day they are not used as often as the fuel of the next category. Distillation fuels include (MGO) Marine Gas Oil and (MDO) Marine Diesel Oil.

- Residual fuel

This type of fuel is high in pollutants such as sulfur dioxide, however, is the cheapest liquid fuel, which makes it fuel used extensively in shipping to date.3.5% of the substance is sulfur oxides. To this category belongs heavy fuel oil. The main categorizations according to the sulfur content are the following:

Table 1: Main categories of marine fuel according to the sulfur content

Marine fuel	Max. Sulfur Content
High sulfur fuel oil (HSFO)	3,5%
Low sulfur fuel oil (LSFO)	0,5%
Ultra-Low sulfur fuel oil (ULSFO)	0,1%

Source: https://www.e-education.psu.edu/fsc432/content/sulfur-and-nitrogen-content

1.2.4 Effect of factors on fuel consumption

In a market where operating margins are constantly shrinking; it is understandable that every shipowner strives to operate his fleet as efficiently as possible in terms of fuel consumption. During a ship's operation, the hull anti-pollution system becomes less and less effective. Abrasion resistance is increased by hull pollution. The total resistance can increase significantly during the time between two tanks due to ship hull marine plant growth, with an average typing speed reduction of about 2-4 percent per year. Controlling the performance of a vessel is becoming increasingly important due to growing concerns about environmental regulations and lower profit margins in the shipping sector. The modern trend necessitates the analysis of large amounts of data. This means that the vast amount of data available for analysis by the ship's supervisor, which comes from various measurement systems onboard or from different sources, has a high degree of breadth and complexity, is produced at a very high rate, and the degree of reliability of the data collected for analysis varies. To reach reliable conclusions, it is necessary to install permanent data collection equipment on board as well as a system for data analysis onshore.

1.2.5 Speed of the vessel

Speed and fuel consumption are two critical factors in the ship's performance, determining the result for the charterer. To secure a good freight, the shipowner will try to describe the ship's speed as much as possible improved and fuel consumption less than the actual (effort occurrence of reduced consumption has recently been abandoned in the long-term charters due to high fuel prices). The charterer, on the other hand, is required to realize these two elements in absolute terms numbers to achieve the profit he budgeted when he made the charter negotiations.

The shipowner guarantees strict adherence to these two elements (speed and fuel consumption), violations of which result in financial penalties. The shipowner declares in the charter agreement that his ship can sail at full load and in pleasant weather conditions at about X miles per hour and with a consumption of about X tons of fuel oil and diesel oil per day. As a result, in clear weather, the chartered ship must perform at an "about" number of miles per hour rather than an absolute number. Empirically, the "approximately" allows for a half-knot deviation for speeds of 10-15 knots, or 3 - 5% of the specified number. However, this margin is not an unbreakable rule because, according to the London Commercial Court, it must be tailored to the shape of the ship, its size, its depth, its behavior, and so on. The English and American arbitrators have accepted the shipowner's one-sided interpretation, which always means less and never more.

For all the reasons mentioned above, optimizing fuel consumption at both economic and environmental levels is extremely important. For this to happen, the proper processing of both mechanical and weather data is necessary. The present work examines these factors and draws some conclusions from real data.

2. LITERATURE REVIEW

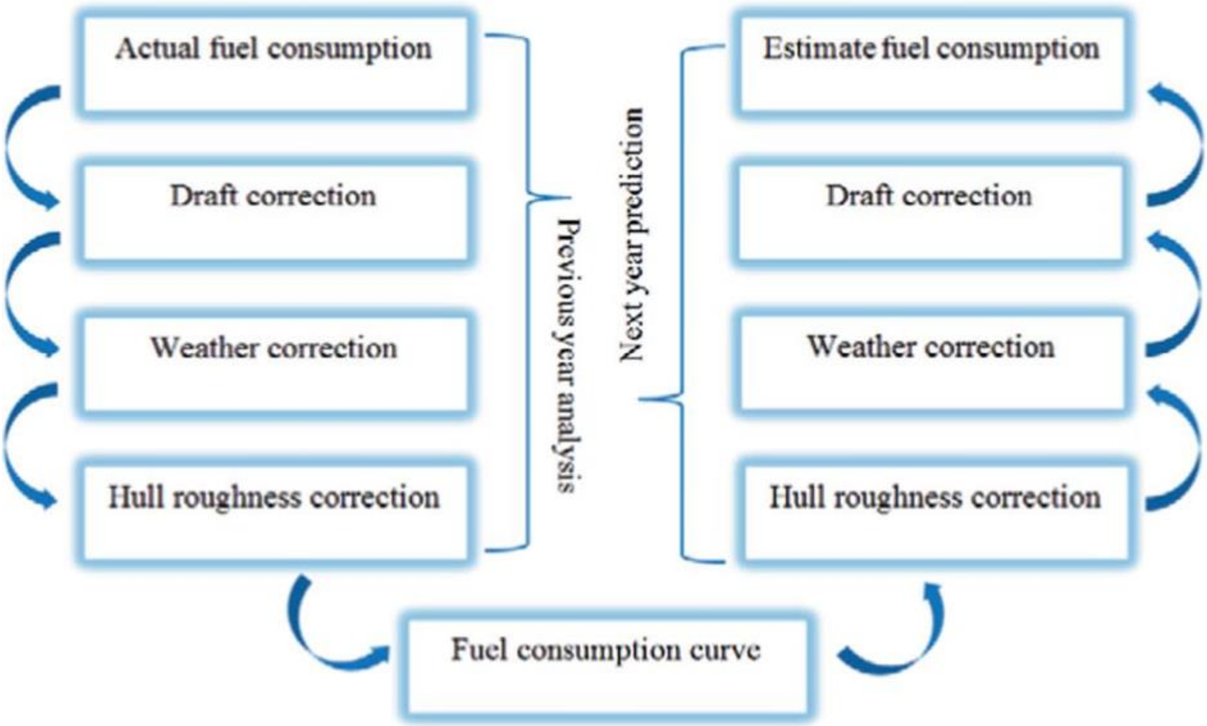
Many theories and methods for estimating the contribution of each of these parameters to increased resistance and fuel consumption can be found in the literature. However, most rely on experiments resulting from a series of tests on specific ship types and hull forms. It is therefore advisable to conduct a continuous statistical analysis of the voyage to investigate the influence of ship sinking, weather, and the condition of the hull and propeller on the production of the fuel consumption curve versus the velocity curve, which represents a more realistic and precise approach to modern ships, as required. Such an approach assumes that forecasts based on last year's performance are more accurate and reliable than those based on sea trials.

By calculating the fuel consumption and speed curve with a high degree of accuracy, it is possible to achieve a more reliable estimate of the fuel required on a future voyage or even for a sister ship. A simple example to assess the importance of establishing such a method can be made considering that the main financial burden of the shipowner under time chartering is the cost of fuel and that 280 annual operating days are consumed at a consumption of 50 tons per day at a cost of 400 USD / ton. An error of 5% in fuel calculations easily reaches 280,000 USD / year, i.e., about 770 USD / day increase in their operating costs. Therefore, a small deviation in the fuel calculation is immediately reflected in an operating cost significantly higher or lower than expected, which means that shipowners can reduce or increase their expected revenue accordingly. For this reason, it is necessary to make decisions based on the best possible fuel consumption forecasts, especially today due to the reduced profit margin for shipping companies and the interest in operating low-CO2 ships.

Zhao et al. (2015) presented a simulation model of the overall propulsion system of a ship. The modeling was done in a MATLAB / Simulink environment and concerns the propeller and the main engine. They used a mid-cycle model to describe the intake/exhaust system, the supercharger, and the engine operation. The ship's axle system was modeled using the power balance and system performance. In the results obtained on fuel consumption, engine power, and ship speed there was a discrepancy between actual prices and expectations. This is because the authors have not considered the auxiliary engines of the ship used and the inaccurate forecast of ripples and weather conditions in general.

The central idea of Bialyostocki and Konovessis, (2019) study, is that shipowners have enough information about the ship's performance from noon reports. Therefore, this data can be used and updated from year to year, instead of estimating fuel consumption based on sea trials plus a margin of tolerance. The methodology followed by the authors for the prediction of the fuel consumption and speed curve is summarized in figure 2.

Figure 2: Outline of fuel consumption curve forecasting process.



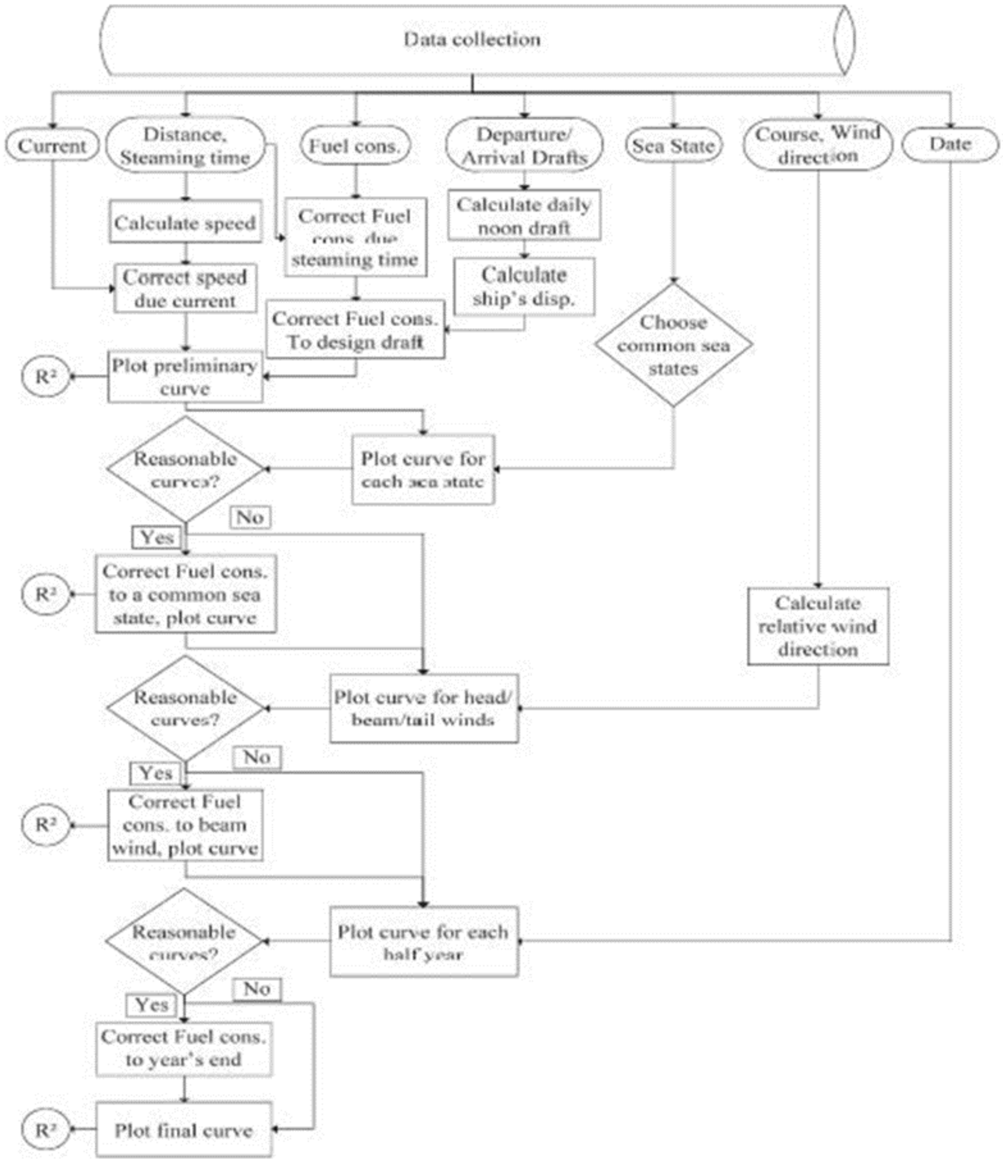
Source: Author

For this purpose, four parameters were evaluated:

- Ship sinking on the voyage understudy
- Wind intensity
- Wind direction
- Date of the upcoming trip

The draft was calculated from hydrostatic panels and stability tables, while the input was the predicted load weight and its separation in the load depots. The weather forecast was used to predict the intensity and direction of the wind, while the date of the expected trip was also required to calculate the fuel consumption. On this basis, the following figure 3 illustrates the algorithm developed for predicting the fuel consumption and speed curve.

Figure 3: Outline of fuel consumption curve forecasting process



Source: Author

Using the final curve obtained through the algorithm described in the previous figure, it was possible to estimate the fuel consumption on a future trip, based on predefined information.

Two of the main advantages of the algorithm developed by N. Bialyostocki, and D. Konovessis are its simplicity of the application as well as the acceptable accuracy of the results obtained regarding the estimation of fuel consumption.

In the study of Lokukaluge et al. (2016) a selected set of data related to shipping performance is analyzed: ship ground speed, route, fuel consumption, main and auxiliary engine power, main engine shaft speeds, loading and sinking conditions in relation to the route, voyage and the intensity of the wind. However, the required corrections in the parameters have not been considered to remove the effect of air current and waves from the velocity-power data, due to the unavailability of the same velocity conditions on a repetitive path with the same environmental weather conditions. conditions. In addition, the ballast condition of the ship has not been integrated into this selected data set.

Corradu, et al. (2020) expand the forecast of a ship's fuel consumption based on data measured by the ship's automation systems. They presented three models for forecasting. White Box Model-WBM, Black Box Model-BBM, and Gray Box Model-GBM. WBMs are based on knowledge of physical processes while BBMs are based on statistical inferences based on data from the past. Finally, they present two different GBM models which utilize the mechanical knowledge of physical principles and the available measurements. Based on previous models, a new strategy is proposed to optimize the energy efficiency of a ship.

In another study, Perera, and Mo (2016) aimed to develop an appropriate data management framework from various sources related to shipping navigation, to overcome the current challenges of its performance under various weather conditions. The proposed data handling framework consists of two main sections, pre-and post-statistical data analysis. The pre-processing part is an on-board application and consists of detecting and diagnosing various errors in the sensors, classifying the data as well as their compression processes. This pre-treatment can improve the quality and reduce the amount of data to be transmitted to land data centers. The on-site data processing section includes expansion steps, integrity, and reliability verification as well as data regression. In this way, they improved the visualization of the data representing the ship's performance. Through the correlation of wind speed and ship performance, it was possible to develop mathematical models for evaluating ship performance.

In a subsequent study, Perera, and Mo (2017) proposed the analysis of data from the operation of the main engine as part of the Ship Energy Efficiency Management Plan

(SEEMP). SEEMP imposes various emission control measures to improve the energy efficiency of ships, considering ship performance data and navigation data. The proposed data analyzes are developed in the motor-propeller combination diagram (i.e., a propeller shaft with a main direct drive motor). Therefore, these data analysis can monitor ship performance and navigation conditions in relation to engine operating areas as part of SEEMP.

Lashgari, Akbariand Nasersarrat (2021) invented a new model for simultaneously optimizing ship routes, sailing speed, and fuel consumption in a shipping problem under different price scenarios. The optimal solution of this model can be used to decide on the average bunkering quantity required to complete the service, the refueling ports, the best type of ship, the appropriate number of ships to complete the route, and the average sailing speed with a view to the time window. The proposed model incorporates possible costs resulting from waiting and delays in ports and considers the port service times when making speed decisions. The ship starts moving from the origin port and seeks the best route to serve all ports. During the route, the ship's fuel inventory level is inspected and if the inventory level is less than the ordering point, it will refuel. It should be noted that there is a penalty cost for running out of fuel along the way. This model also provides a non-linear cubic function for fuel consumption that depends on the sailing speed and size of the ship. Sailing speed can change because of adapting to the time window, so some constraints and a penalty cost are considered to control this violation.

Wang, Lang, and Mao (2021) used a voyage optimization method combining a genetic algorithm and dynamic programming for fuel/emissions reduction. The proposed method is capable of multi-objective global optimization to reduce fuel emissions and can provide recommended sailing route and engine power setting along the voyage as direct outputs to guide practical ship navigation. About 5% fuel-saving and air emissions is achieved by the method than the measured fuel cost.

Qi and Song (2012) tried to minimize fuel emissions by optimizing vessel schedules in liner shipping with uncertain port times. They aim at seeking the optimal vessel schedule in the given shipping route by minimizing the total fuel consumption (or emissions), in which uncertain port times at each port-of-call and the frequency requirements on the liner schedule are considered. Due to the cumulative effect of uncertainties at port-of-calls, the general optimal scheduling problem appears to be analytically intractable. They therefore use simulation based stochastic approximation methods to solve the problem. They concluded that the short leg is the one that has the biggest problem when designing the optimal schedule and the legs with longer distance should have a larger leg-transit times.

Chang and Wang (2014) presented a study which focused on the use of speed to reduce the cost in short-term voyages. The best scenario was the one in which fuel costs were high and charter rates were low and the speed reduction depends on charter rates and fuel prices. The first step of the model determines the optimal trade-off between fuel costs and costs resulting from the delays. Secondly, comes the confirmation that the engines can run efficiently for long routes at reduced levels. Last, shippers should ensure that the speeds are sufficient to meet demand to avoid using more vessels.

Caraddu et al. (2017) presented three different approaches for the prediction of the fuel consumption by analyzing real data for a Handymax chemical/product tanker. The authors proposed a trim optimization technique which exploits the predictive power of the proposed models for the online selection of the best configuration of the trim for reducing the fuel consumption.

Psaraftisand Kontovas (2014) published an article about ship speed optimization. The goal of this work is to clarify some key difficulties in ship speed optimization at the operational level and to construct models that optimize ship speed in a single ship setting for a variety of routing scenarios. The paper's key addition is the inclusion of those fundamental metrics and other aspects that weigh strongly in a ship owner's or charterer's speed selection and, when applicable, in his routing decision. Several examples are presented to show the features of the best solution as well as the numerous trade-offs involved. The study found that options for optimal environmental performance are not always the same as those for optimal economic performance. Also, measures that appear to be ideal from an environmental standpoint at first look may fact be suboptimal. The authors suggest the addition in future research of different fuel consumption functions for different legs of the route, say, due to different average weather conditions, sea currents, etc.

Friske, Buriolaand Camponogara (2022) dealed with a relax-and-fix and fix-and-optimize algorithm for a Maritime Inventory Routing Problem. This paper gives an overview of the solution approaches proposed for various MIRP variations, with a particular focus on metaheuristic methods, which combine heuristic and optimum approaches and are commonly employed to solve MIRPs. This research also looks at how Relax-and-Fix and Fix-and-

Optimize metaheuristics can be used to solve a specific MIRP variant that has been offered in the literature. When considering time and solution quality, the computational results showed that the proposed algorithms perform better when using the FCNF formulation. The TS model also yielded some promising findings. Even though no possible solution was identified in certain circumstances, the proposed approach was able to get new best-known values in others, illustrating the problem's potential effectiveness and its reliance on a good choice of parameters for each instance.

Mad, Zhange and Wangc (2021) provide a multi-objective optimization approach for maritime regulators, such as those working in marine departments, to achieve a trade-off between total ship costs and total CO2 and SOx emissions. The route and speed multi-objective optimization problem was solved using the NSGAII algorithm and the TOPSIS ranking method. As a case study, a service route along the East Coast of the United States was chosen. The results show that the proposed strategy produced the optimal routes and speeds while also balancing total costs, CO2 emissions, and SOx emissions. A sensitivity study revealed that the suggested strategy might efficiently balance SOx emissions both inside and outside ECAs, as well as assist maritime businesses in avoiding quick increases in sailing expenses as LSFO prices rise. Furthermore, the proposed strategy can help to decrease the pressure on shipping companies to increase LSFO pricing after the adoption of sulfur restriction legislation in 2020 by avoiding significant increases in total costs commensurate with increases in LSFO prices. The authors state that they have no known competing financial interests or personal ties that could have influenced the research presented in this study.

Gino and Shib (2020) presented a study about Stimulating sustainable energy at maritime ports by hybrid economic incentives: A bilevel optimization approach. In the competitive setting of an area with several ports, this study presents a novel hybrid economic strategy to aid both the regulatory authority and stakeholders of port companies in striking a balance between energy sustainability and fair competition. The proposed approach appears to be capable of efficiently promoting green energy and decreasing emissions while maintaining port customers' welfare and long-term growth, according to simulation findings. It can be inferred that carbon tax is a more effective technique for emission mitigation than incentive after looking at numerous combinations of tax and incentive policies in both case studies. In fact, when there is no tax, greater incentive rates are required to encourage the use of sustainable energy alternatives, but even low tax rates can provide the adequate impetus for ports. Furthermore, combining a tax and an incentive can improve performance and increase motivation to reduce emissions. In terms of green solution selection, our findings show that the port favors options that strike the correct balance between emission reduction and overall cost. For example, in their case studies, ports have invested more in onshore power supply because of its great effectiveness in reducing emissions at a relatively modest investment cost.

To realize a more convenient link Jurcevic (2015) present the development of a mathematical model is proposed as the basis for decision making optimization of data traffic route in maritime vessel communication. In addition to presenting previous research, the paper demonstrates the optimization of data traffic routes within the organizational environment using the example of authentic maritime communications. The article includes an authentic ship voyage data example for the container ship OOCL Netherlands on her voyage number 30W34 in 2012. According to transatlantic route analyses, the ship spent 27.8 percent of her total sail time in the range of terrestrial links. The availability of terrestrial links is expected to be even greater on shorter journeys with more ports along the route. The paper demonstrates the need for internet traffic to be routed via terrestrial providers rather than expensive and volume limited satellite providers. It is possible to create a mathematical model of maritime vessel data traffic using Markov chain theory. Model-based simulation in MATLAB can also be used to optimize data traffic routes.

A mathematical model for optimizing investment decisions and the operation of battery units on maritime vessels has been presented by Bordinand Mo (2019). The paper demonstrates a methodology for incorporating relevant safety and operational constraints, as well as storage degrading effects, into investment decisions. This includes a variety of vessel operational modes, bus-tie breaker operation philosophy, and spinning reserve requirements. An implementation of the proposed model was used to run a storage investment analysis for a vessel equipped with four diesel engines. The case studies presented in the paper were designed to demonstrate the wide range of sensitivity analyses that can be performed with the proposed model, as well as the high potential of such a tool for those in charge of investment decision making. It was demonstrated how different safety constraints and operational mode combinations influence the investment analysis. The case studies demonstrated that many different dataset combinations can interact with one another and influence final decisions. The decision-making process is thus extremely delicate and difficult, necessitating the use of appropriate tools capable of addressing the various needs and constraints in a holistic manner that would not be possible with other manual approaches. As a result, a holistic approach provided by optimization techniques is critical in order to find a suitable solution capable of meeting all operational requirements while also taking into account all critical system properties. The model decisions are seen to be very sensitive to the vessel's modes of operation; therefore, researching ways to mathematically describe such operations is a critical contribution for the scientific community attempting to analyze such systems. The authors propose that the proposed methodology for energy storage sizing can be used as a stand-alone tool or integrated into vessel design software tools to optimize larger parts of the vessel design.

The ship fuel consumption data from two voyages were collected and processed in the study of Huet al. (2022) using various sensors. Following that, a hybrid fuel consumption prediction model is proposed by combining several state-of-the-art single models based on the processed data and the hyper-parameter tuning method. Finally, the hybrid model was used to optimize ship trim in order to save fuel and reduce emissions. The main findings of this study have been summarized as follows.

- Data processing improved the performance prediction of all models moderately. The model performance improved from a reasonable or good forecasting level to a highly accurate forecasting level, according to the MAPE metric.
- The model's performance prediction is also affected by hyper-parameter optimization. The model's predictive performance potential was further enhanced by hyper-parameter optimization.
- The proposed hybrid model outperforms all single models in terms of accuracy and robustness. Using the MAPE metric as an example, the hybrid model improves accuracy by 0.20 percent –54.08 percent for Voyage1 and 0.64 percent –57.53 percent for Voyage2. Furthermore, it improves robustness by 12.15 percent –58.09 percent and 9.46 percent –73.57 percent in Voyage1 and Voyage2, respectively.
- Trim optimization can significantly improve a ship's energy efficiency. In Voyage1, the fuel saving, and emission reduction ratios of PO value are 1.82 percent, 1.82 percent, and 1.58 percent, respectively, when compared to the RC value, PC value, and PL value. In Voyage2, their respective ratios are 0.69 percent, 0.68 percent, and 0.77 percent.

In the first step of this two-step strategy, the proposed hybrid model can enrich the fuel consumption prediction model library. Following that, the proposed trim optimization method in the second step can provide more feasible operational methods for saving fuel and lowering emissions. The trim optimization model, on the other hand, assumes that a ship's trim can be changed in real time. In fact, ships find it difficult to change their trim states frequently (5 minutes per time). As a result, the authors propose that more constraints, such as changing the trim value once a day, be considered in the future for more realistic and reliable trim optimization results.

Ulsrud et al. (2022) investigated an operational planning problem arising in the offshore oil and gas industry, in which we determine routes and sailing speeds along these routes for a set of platform supply vessels (PSVs) servicing a given set of delivery and pickup orders at offshore installations while minimizing costs. The sailing costs, which are primarily caused by fuel consumption for PSVs, are heavily dependent on the chosen sailing speeds. Furthermore, the fuel consumption and possible speed ranges for PSVs are heavily influenced by changing weather conditions. As a result, a weather- or time-dependent vessel routing problem with speed optimization is generated (TDVRP-SO). Optional decisions include deferring certain orders and chartering spot vessels, both of which incur additional costs. On a time-space network, a mixed integer programming (MIP) model for the TDVRP-SO has been developed. We proposed an Adaptive Large Neighborhood Search (ALNS) heuristic for the TDVRP-SO because the MIP solver is limited to solving instances with at most 16 orders for 13 offshore installations within a reasonable time limit of one hour. To improve initially constructed solutions, the ALNS heuristic employs an adaptive selection of destroy and repair heuristics, some of which are problem-specific heuristics based on offshore logistics planning characteristics. Furthermore, two extensions are introduced to improve the ALNS heuristic's performance: local search and a set partitioning model that selects useful combinations of voyages from previous ALNS iterations. When compared to the more common approach of applying a fixed design speed for each voyage, the experiments show that including speed optimization results in significant cost savings and CO_2 emission reductions of approximately 20%. In addition, three scenarios for forecasted wave heights were used to examine the impact of weather conditions on planning. The findings emphasize the importance of considering the correct weather conditions when scheduling voyages, as otherwise, the solutions may significantly underestimate the true cost of carrying out the planned voyages under actual weather conditions. Ignoring weather conditions in planning may even result in some orders being unable to be serviced due to weather-induced delays in actual schedule execution.

Liaet al. (2020) published a study about vessel traffic scheduling optimization for the restricted channel in ports. This paper abstracts a general structure of a restricted channel in multi-harbor basins and pinpoints four key areas of vessel traffic conflict based on an analysis of VTSP existing in ports with multi-harbor basins sharing a restricted channel. Then, to solve the problem, a mathematical model of multi-objective optimization is proposed. An NSGA-II-TS algorithm with five layers of integer coding is proposed to obtain the vessel sequence and the optimal traffic scheduling schemes, considering the number of vessels, navigational direction, navigational mode, harbor basin location, and berthing location. Furthermore, it provides a solid theoretical foundation for studying vessel traffic scheduling optimization for restricted channels in multi-harbor basins, as well as providing VTS operators with auxiliary decision-making from the perspective of ports and vessels. Without limiting its applicability, the proposed method can be applied to other narrow restricted channels to provide insight into vessel traffic in inland waters or straits. This paper is only a preliminary investigation and does not consider factors such as weather conditions, the uncertainty of port operation plans, changes in vessel arrival and departure times, tug scheduling preparation, and pilot assignment.

The uncertainty of ice loads and water velocity in single and multiple segments in the vessel speed optimization design process is addressed in the study of Yeping et al. (2021). The involved factors' random statistics distribution models are then introduced into the interval optimization system, and their randomness is examined. To investigate the impact of uncertainty, a series of cases are tested, each with a different interval radius, algorithm, and other configuration parameters. The effect of parameter uncertainty on the energy efficiency of a vessel sailing in an ice area is generally revealed by calculating a series of cases, with a 15% reduction in EEOI. The interval method is reasonable and superior due to the high randomness and mutation of ice loads. Furthermore, the introduction of probability parameters into interval optimization increases input uncertainty, resulting in an output response based on a specific probability. An uncertainty analysis can reveal the probability influence of different analysis methods and a series of interval radius on the results and then guide the practical application. Finally, the practical performance of energy efficiency interval optimization can be improved by further developing the multidisciplinary calculation or simulation model used in the energy efficiency index and introducing the interval optimization method, which has a more complex nested structure.

When floating macro-marine debris enters the ocean, it becomes a global environmental problem. The study of Duana et al. (2021) deals with it. It harms the marine ecosystem, endangers human health, and results in incalculable economic losses. Marine debris has been transported to various locations over time because of ocean currents and winds, and a time window cannot be ignored when navigating the locations of marine debris. To effectively mitigate the risk, the authors propose optimizing vessel routing with a time window for collecting and removing marine debris. They begin by using GNOME software to determine the debris trajectory and establishing a time window for each debris location. To reduce total debris collection costs, a mixed-integer nonlinear programming model that takes vessel velocity into account is proposed. To solve the proposed mathematical model in a reasonable timeframe, they propose two customized solution approaches: the Branch-and-Cut (B&C) algorithm and a two-stage Adaptive Large Neighborhood Search (ALNS) based heuristic algorithm. The proposed model and solution algorithms are validated using a computational study in the waters off Boston. The results show that the average optimality gap for the GUROBI and B&C algorithms is 17.53 percent and 10.52 percent, respectively, while the ALNS algorithm has a gap of only 3.44 percent. Furthermore, the ALNS algorithm's average computing time is roughly 24 and 17 times faster than the GUROBI and B&C algorithms, respectively. The experimental results show that the distance from the location of the debris to the harbor is positively related to the collection cost and negatively related to the average usage of vessel capacity, and debris dispersion is also positively related to vessel fuel consumption.

To recover heat energy from a natural gas engine Ouyang et al. (2022) combined an over-expansion transcortical CO2 cycle with a double effect absorption refrigeration cycle. Simultaneously, a post-processing unit for removing flue gas nitrogen oxide is proposed. The MOPSO program coordinates the optimization of residual equivalent output work, payback period, and NOx reduction. Furthermore, the required and attained EEXI values are calculated. The authors concluded that increasing engine load reduces the combined cycle's exergy efficiency and environmental performance while increasing equivalent output work, equivalent thermal efficiency, and economy. Furthermore, depending on the power generated by the WHR cycle, the post-processing unit generates certain economic benefits by removing NOx and synthesizing ammonia, which can reduce the total system's payback period. Finally, the final optimization results are obtained using the MOPSO program, with the residual equivalent output work, payback period, and NOx reduction of the total system being 150.77 kW, 4.20 years, and 8.16 g/kWh, respectively.

Theodoropoulos, Spandonidis and Fassois (2022) published a study about the use of Convolutional Neural Networks for vessel performance optimization and safety enhancement. A two-dimensional convolutional neural network classifies contour images derived from a dataset acquired from sensors located on a Bulk Carrier in the current work. The genre of 2D CNNs that monitors the efficiency of the ship by inspecting images representing the ship's performance and attempting to detect efficiency degradation was critically presented. In contrast to applications presented in relevant literature in which the 2D CNNs received spectrograms, the lack of high-frequency data rendered such an option infeasible on this occasion, prompting us to investigate the contours. In addition, a parametric investigation of the effect of multiple variables on model performance was presented in an attempt to determine the impact of the induced degeneration levels and how accurately different levels of degradation would be detected, as well as the effect of the input time interval on the efficacy of the proposed network. It was shown that, intuitively, the proposed methodology became more effective as the degree of degradation increased. In contrast to the presented benchmark ML classifiers, which could not identify defective patterns for small degenerations, it could be claimed that all examined levels of artificially generated deficiency were adequately detected. In terms of the input time intervals of the two methods, it was determined that the long-term FD scheme performed better as the window size increased.

Liuet al. (2020) presented a model predictive control for path following and roll stabilization of marine vessels based on neurodynamic optimization. Wave-induced roll motion can have a negative impact on ship comfort and stability, increasing the risk factor and safety concerns in harsh environments. Rudder roll stabilization (RRS) is an appealing solution for reducing roll motion because it requires no additional devices or space on a ship (Amerongen et al., 1987 & 1990 Oda et al, 1992 & 1996 Perez, 2005 Kapitanyuk et al, 2016 Wang et al, 2017). The traditional RRS problem is extended in this paper into the integrated problem of path following and roll stabilization, which is more advanced for navigation safety and efficient transportation. In the control design, a neurodynamic optimization system based on PNN is established to solve the objective function formulated by MPC parallelly; this significantly improves the computational efficiency of standard MPC. The objective function incorporates the terminal cost function, which is derived from the Lyapunov equation, to ensure closed-loop stability. The simulation results demonstrated that the controller proposed herein can achieve the goals of path following and roll stabilization at the same time. The authors assume that comparative studies have demonstrated the efficiency advantages of the proposed controller, indicating that the proposed MPC design is promising for use in practical applications. The authors propose that in the future, they will concentrate on conducting research on techniques that will aid in smoothing the rudder motion.

Because of the continuous external power demand, a dynamic multiobjective optimization model for optimal scheduling of diesel generators is generated by Li et al. (2022), taking both fuel consumption and greenhouse gas emissions into account. For each time step, the study proposes a two-phase analysis framework. The scheduling of power generation is investigated from the perspectives of dynamic multiobjective optimization and multi-attribute decision making. In addition, multivariate analysis (SOM, Clustering, MDS, and regression) is used to investigate the characteristics of the power generation scheduling process. For dynamic power generation scheduling, a general analysis flowchart is proposed, and the Pareto set is obtained through a multiobjective optimization approach, followed by the necessary decision-making process. MVA can discover hidden information about a data set after a history of loads and performances has been collected. The study concluded that MOALO is an algorithm with enhanced exploration and exploitation capabilities. It is appropriate for resolving the problem of power generation scheduling. When compared to other heuristic methods for this scheduling problem, the superiority of its single objective version, ALO, is also demonstrated. MOALO consumes less time and has the potential to be used in real-time applications of power generation scheduling problems. In addition, SOM with clustering analysis can group samples based on time, mining features of small clusters via visual projections. MDS can discover the mutual relationships between performances. MVA results add to our understanding of the DMOP model.

Nublia, Sohnaand Prabowo (2022)proposed an optimization framework for the FGSS layout, which is installed in a hypothetical LNG-fueled ship model. The separation distance was used for MINLP optimization. As an optimization tool, Mixed-Integer Nonlinear Programming (MINLP) is provided. The Python programming language is used to create the MINLP framework. Several points about the MINLP model are summarized below.

- In the MINLP formulation, problem statements have been presented. It includes the equipment position, which is set as a variable. As a constraint, the deck size, minimum separation distance, and non-overlapping functions are used. In this objective, the total pipe length function is used, which is made up of equipment distance values and a connectivity function. The MINLP framework is built using a Python script.
- The MINLP solution satisfies all constraints that reduce total pipe length. By specifying an appropriate separation distance and lowering the pipe cost, four feasible layouts were generated. As a limitation, the MINLP model only works perfectly in ideal conditions. To simplify the optimization problem, the valve, elbow, and pipe routing curving were not installed. As a result, after obtaining the feasible layout, pipe routing is still required. Nonetheless, the MINLP result's feasible equipment distance reflected an optimization goal of finding a shorter pipe route.

Pawel, Defrynand Grigoriev (2020) introduced, a local-search-based heuristic for the lock scheduling problem on a river network, and the known mathematical programming formulation of is extended to include more realistic features and conditions of the problem. Using computational experiments on real AIS dataset from a section of the Dutch river network, the heuristic algorithm and a straightforward implementation of the mathematical formulation were compared. The mathematical programming formulation is incapable of dealing with large real-world examples. As a result, the proposed heuristic has the potential to become an algorithm for lock operators and vessel captains to use to regulate lock congestions and adjust sailing velocities to optimize fuel consumption and CO2 emissions. Furthermore, the authors assessed the impact of changing the service level and processing time of lockage on the total fuel consumption of the vessels. It is assumed that vessels may miss their assigned lockage due to unforeseen circumstances such as a delay in arrival time into the system or a delay within the system. The authors state that their findings are based on the strong assumption that overtaking is permitted on the rivers under consideration. In practice, however, due to narrow river segments or traffic regulations, this may not always be possible. The integration of such features is of theoretical and applied values and has not been considered previously.

Norlunda and Gribkovskaia (2017) investigated how weather affects the use of speed strategies in supply vessel operations. They created a simulation-optimization tool to evaluate the performance of speed optimization strategies while taking weather into account. This tool is made up of three main procedures. The first procedure is to generate feasible, speed-optimized journeys. The second procedure simulates speed-optimized voyages to evaluate voyage duration and fuel consumption under various weather conditions over a given planning horizon. The third procedure involves calculating the expected average fuel consumption for schedules generated by iteratively solving an optimization model based on simulation results. Winter weather increases weekly schedule fuel consumption (12 percent on average) and the number of vessels used, according to real-world experiments. The use of speed optimization strategies while taking weather into account allows for a significant reduction in fuel consumption. Their tests show that, despite the weather impact, it is possible to reduce schedule fuel consumption by 19% using the recursive speed optimization strategy in January, and by 9% using speed reduction on voyage legs with waiting time. It is concluded that the environmental performance of speed optimization strategies in the winter months is very similar to their performance in ideal weather, implying a 2% reduction in average fuel consumption and a corresponding reduction in emissions. However, using speed optimization during the winter season may result in schedules with extra vessels, resulting in higher vessel costs. This is consistent with the literature on emissions reduction in maritime transportation, where slow steaming and rough seas may result in an increase in the size of the vessel fleet.

Lazakis and Khan (2021) propose an optimization framework for the daily operational planning of an offshore wind farm's maintenance fleet. The framework includes a heuristic optimization technique that was developed and integrated. The new framework optimizes the entire maintenance task sequence in order to reduce overall fuel consumption and expand the operational window of the wind farm. Climate data, such as average significant wave height and average wind speed for a given day, are used during the optimization process to plan a single weather window. The framework also takes into account inputs such as vessel specifications and fuel consumption. CTVs (Crew Transfer Vessels) and SOVs (Service Operation Vessels) are optimized separately, and the entire maintenance operation task is divided into two sessions: pick-up and drop-off. The framework optimally plans the drop-off session first, and then, if necessary, the pick-up session. The total fuel consumption for a given day is computed by adding the fuel consumption from both sessions. The framework's reliability and feasibility were tested using a variety of test cases, and it was discovered that the new framework can significantly reduce overall fuel consumption while also increasing the operational window. It was also discovered that when SOV and CTVs are used together, the operational window expands.

Duan and Zhang (2020) use vessels with Hybrid Energy Systems (HES) of Photovoltaic (PV), battery packs, and diesel to clean up macro-debris offshore to mitigate the damage to the environment and human health caused by MD. To implement an economical and efficient cleaning scheme, a two-stage optimization method is proposed. The first stage uses a VRPTW model to minimize travel time, which is solved by a customized ALNSPHR algorithm. Remote sensing technology and GNOME software are used to determine MD's location on the sea surface. In the second stage, a MILP is used to optimize the vessel's EMS with the goal of minimizing total cost while keeping power load balance, battery charge and discharge state, and output limit of each energy source in mind. A set of different scale examples show that the ALNSPHR algorithm outperforms the VRP Spreadsheet Solver and the CPLEX solver in terms of computation time and results. They divide the PV output into four different scenarios based on the intensity of the lighting and compare the costs for each scenario. Each energy's OPF is calculated. Some important conclusions have been reached: (1) In terms of cost and carbon emissions, HES is significantly better than pure diesel fuel systems, and the task is performed during times of high illumination intensity. It's a good idea to complete tasks during high-light hours. (2) In the beginning, the more power stored in the vessel's battery packs, the better; (3) Diesel charges battery while also powering load; (4) Even when the life-cycle carbon emissions of batteries and diesel are considered, there is no effect on cost savings.

Marine debris collection is beneficial not only to environmental protection but also to resource recovery and societal development. The logistics network is used in the study of Duan et al. (2021) study to optimize vessel routing for debris collection by developing a mixed integer linear programming model. To solve this model, a hybrid algorithm of adaptive large-scale neighborhood search and wolf pack algorithm is proposed. Finally, an example is used to validate the model's correctness, and the proposed algorithm's efficiency is demonstrated by comparison with ALNS and CPLEX. Following computation and analysis, the authors reached the following valuable conclusions. (1) Selecting the best time to collect debris can significantly reduce costs and travel time. It is most advantageous to collect debris drifting on the surface of seawater when it is closer to the port and more concentrated. When we assigned the vessels to collect debris, the total cost and travel time could be reduced by up to 6.38 percent and 8.88 percent, respectively, when compared to the worst-case scenario. A total cost savings of approximately $75,590 per calendar year. (2) By selecting the appropriate vessel type, the total cost can be effectively reduced. In the example, we obtained the lower bound of the vessel's capacity and discovered that travel time was inversely proportional to vessel capacity. It is concluded that a vessel with a capacity of 12 tons is the best vessel type for this example, reducing total costs by 2.65 percent and travel time by 6.81 percent when compared to the vessel type of 10 tons previously given. (3) Assuming that the weight of each debris does not exceed the vessel's capacity, the total cost, collection route, and number of vessels used are unaffected by the increased weight of light debris. Even with a 45 percent weight increase, 71.69 percent of debris has a total cost growth rate of less than 1%. When the total cost increase is less than 0.1 percent, the collection route remains unchanged. When the weight of the debris changed, the number of vessels used remained constant for 42.86 percent of the debris. When an additional vessel is required, the total cost rises by 1.23 percent on average.

Meta-heuristic optimization algorithms seek to solve real-world problems by maximizing certain criteria such as performance, profit, and quality while minimizing others such as cost, time, and error. Housseinet al. (2021) propose I-AOA, an improved version of the Archimedes optimization algorithm (AOA). To improve the performance of the original AOA, two efficient strategies are used: local escaping operator (LEO) and orthogonal learning (OL). The CEC'2020 test suite and three engineering design problems—tension/compression spring, pressure vessel, and rolling element bearing—are used to evaluate the I-performance. AOA's To the best of our knowledge, this paper is the first attempt to use the AOA to estimate the parameters of two types of fuel cells: 250 W PEMFC and BCS 500 W. The obtained polarization curves of the fuel cells were well-matched with their corresponding experimental datasets using the proposed strategy, indicating the method's perfection in both cases. In comparison to the other methods, the I-AOA optimizer achieves the lowest standard deviation, the lowest mean RMSE, and the highest coefficient of determination. In addition to the above-mentioned benefits, the optimizer demonstrated lower computational complexity. It is worth noting that the proposed I-AOA method can be recommended as an accurate optimization technique for estimating fuel cell parameters under any testing conditions.

Table 2 summarizes the optimization works relative to this study.

Table 2: Research studied on optimization by author

KIND OF OPTIMIZATION	AUTHORS
Fuel Consumption Optimization	Feiyang Zhao et al. (2015) N. Bialyostocki, D. Konovessis (2019) Andrea Caraddu, Luca Oneto, Francesco Baldi and Davide Anguita (2017) Julian Arthur Pawel, Golaka Christof Defryn and Alexander Grigoriev (2020)
Performance Optimization	Lokukaluge P. Perera and B. Mo (2016) Panayiotis Theodoropoulos, Christos C. Spandonidis and Spilios Fassois (2022) Essam H. Houssein, Bahaa El-din Helmy, Hegazy Rezk and Ahmed M. Nassef (2021)
Speed Optimization	Harilaos N. Psaraftis & Christos A. Kontovas (2014) Yuanhang HouYeping, XiongYonglong Zhanga, Xiao Lianga and Linfang Sua (2021). Ellen Karoline Norlunda and Irina

	Gribkovskaia (2017) Karl Petter Ulsrud, Anders Helgeland Vandvik, Andreas Breivik Ormevik, Kjeti Fagerholta and Frank Meisel (2022)
Fuel emission optimization	Xiangtong Qi, Dong-Ping Song (2012) Weiha Maaf Dongfang Maab Mad, Jinfeng Zhange and Dianhai Wangc (2021) Anahit Molavi Gino and J. Lima Jian Shib (2020) Helog Wang, Xiao Lang and Wengang Mao (2021) TianchengOuyanga, Zhiping Wanga, Wenjun Liua, PeijiaQina and Haijun Mo (2022)
Route optimization	Masha Lashgari, Ali Akbar Akbari and Saba Nasersarrat (2021) Gang Duana, Amin Aghalarib, Li Chenc Mohammad Marufuzzaman and Junfeng Mab (2021) Haris Nublia, Jung Min Sohna and Aditya Rio Prabowo (2022) Gang Duan and Kaibin Zhang (2020)
Cost optimization	Ching-Chic Chang and Chin-Min Wang (2014)

	Weihao Maaf Dongfang Maab Yijia MadJinfeng Zhange and DianhaiWangc (2021)
Ship efficiency management optimization	Lokukaluge P. Perera and B. Mo (2016)
Maritime Inventory Route Optimization	Marcelo W. Friske Luciana S. Buriola Eduardo Camponogara (2022)
Green Energy Optimization and Environmental Impact Optimization	Anahit Molavi Gino and J. Lima Jian Shib (2020) Gang Duan, Tao Fan, Xiaohui Chen, Li Chenb and Junfeng Ma (2021)
Decision Making Optimization	Dean Sumića Dragan Peraković Marinko Jurcević (2015) Chiara Bordin and Olve Mo (2019)
Trim Optimization	Zhihui Hu, Tianrui Zhoua, Rong Zhenb Yongxing Jina and Xiaohe Lic Mohd Tarmizi Osmana (2022)
Traffic Scheduling Optimization	Junjie Lia, Xinyu Zhanga, BingdongYangb and Nannan Wangc (2020)
Neurodynamic optimization	Cheng Liu, Daiyi Wang, Yuxi Zhang and Xiannan Meng (2020)
Operation Optimization	Iraklis Lazakis and Shahroz Khan (2021)
Multi-Objective optimization	Li Xuebin, Yang Luchun, Huang Lihua and Wang Changjie (2022),

Source: Author

As seen, many authors have dealt with optimization in shipping in many different areas such as speed, fuel, green maritime, management, data, etc. Nevertheless, in fuel optimization, there seems to be a gap regarding the influence exerted by weather conditions on fuel. More specifically, Psaraftis and Kontovas (2014) suggest the research of different fuel consumption functions of different legs of a route due to different average weather conditions. Moreover, Zao (2015) made inaccurate forecasts of ripples and general weather conditions. For this reason, he suggests in future research the use of the exact weather conditions to draw more useful and reliable conclusions.

3. METHODOLOGY

The procedure followed for the elaboration of this thesis is summarized in 4 distinct phases:

Phase 1: Study of bibliographic reports on the factors that affect the fuel consumption of a ship

During Phase 1, an attempt was made to collect information from various academic sources in order to create a concise but comprehensive theoretical foundation for future research.

Phase 2: Qualitative analysis of the conclusions of Phase 1, drawing on the experience of experts in the field of Shipping

During this phase, experts who have been studying fuel consumption in real-life scenarios of various types of ships, particularly cargo, tankers, and LNG ships, provided useful information. Because the experience is difficult, if not impossible, to structure and capture systematically in the literature, the contribution of experts in commenting on and drawing conclusions from the current study has been critical.

Phase 3: Statistical analysis of a set of data derived from the actual operation of a fleet of 5 tanker vessels, for the quantitative evaluation of the conclusions of the literature

Through the utilization of real historical data and the theoretical and practical study of their effect on fuel consumption, it was possible to reveal the relationships between the input variables and output.

Phase 4: Conclusions and perspectives

During the last phase of the study, the conclusions drawn from the previous theoretical and practical study were recorded and the perspectives emerging from the present work were examined.

Consequently, the methodology followed and described above, allowed both the confirmation of the theoretical knowledge derived from the study of bibliographic references but also highlighted the problems encountered when studying the actual fuel consumption of a ship in normal operation. Only through the realistic performance of the problem is it possible to approach feasible, useful, and effective solutions.

The research was carried out between June and August of 2020. For the purpose of the study, data from the ships of a large shipping company and the SAP BUSINESS CLOUD program were used.

3.1 DATA MEASUREMENTS AND ANALYSIS

In recent years, there has been a massive increase in the production of data, both structured and unstructured, relating to ship routes, weather conditions, sea conditions, and so on. In this context, the challenge is to collect and analyze data in an appropriate manner in order to generate new knowledge and develop innovative services that will provide value to the various actors involved in the sea and shipping.

Human activities in the marine environment encompass all of the features that define large-scale data. The volume is enormous, the rate at which data is generated is extremely fast as a result of this volume, there is a great variety in nature and structure as a result of the multitude of different activities and data each managed, variability and quality are constantly changing with the development of technology and the need to find new methods, while the value is enormous as the marine environment, and thus the activities and data produced by them, play a critical role in the analysis.

The use of proportions makes complex issues easier to explain and understand. Data on a large scale is no exception. In recent years, the phrase "large scale data" has gained traction. Industries are shifting their business strategies to more digitized models. Entrepreneurs can automatically measure, and thus know, more and more information about their businesses through large-scale data analysis, and can use this knowledge to make better decisions about their performance. managing businesses Large-scale data analysis results in business intelligence and, as a result, business profits.

Big data analysis is based on the following features, commonly known as "4 V's"

1. Volume: The amount of data generated and stored for analysis.
2. Variety: The type and nature of data can vary considerably
3. Velocity: The speed at which data is generated as well as the frequency with which it is processed by analysts

4. Veracity: The quality of the data can vary greatly, thus drastically affecting the reliability of the conclusions drawn.

Source:https://researchhubs.com/post/ai/introduction-to-data-science/big-data-4-v.html

3.2 DATA COLLECTION

A shipping company's data for the performance of its ships may include noon reports, which provide information on the operation of ships on a daily basis, as well as real-time data (live data) which are derived from communication systems and satellite telematics (Inmarsat).

Estimates of the ship's condition, hull, and propeller cleaning requirements, and maintenance or repair work to optimize engine performance can be made based on the quality and quantity of collected data. The accuracy and dependability of the data collected for analysis are critical for reaching sound conclusions. As a result, all metering and recording systems must be checked on a regular basis to ensure proper operation. It is also critical to correctly determine the loading line indications, water temperature, and specific density.

More specifically, the data that must be kept before recording any measurement related to the ship's performance are the following:

- Determining the position of the ship (longitude / latitude coordinates)
- Weather conditions
- Water temperature and density
- Temperature of the environment
- Vertical position of the anemometer above the waterline
- Draft in the bow, stern and middle of the vessel
- Displacement, calculated from the height of the wells
- Conductivity, calculated from the height of the wells
- Transversely projected area above the waterline, including superstructures
- Height of superstructures

To ensure that the wind speed is correctly recorded, it is best to obtain the absolute value as well as the direction from a land meteorological station. It is also worth noting that oceanographic services collect and analyze a large amount of statistical data and weather information (British Admiralty, coastal stations, weather routing companies, etc.). These provide data that is used as a filter in performance analysis and correction.

During the measurements made to check the performance of the ship, the following data must be observed:

- Date
- Time
- Cruising time
- Heading of the vessel
- Relative wind speed and direction
- Ripple period (wave), ripple height and direction
- Medium subsurface ripple period (swell), ripple height and direction
- Average bottom height

The monitoring system should provide all stored information in both tabular and graphical form at the end of each measurement cycle, making it easy to evaluate it in terms of quality and coherence. so that safe conclusions about the ship's performance can be drawn.

The correct analysis of data during sea trials, according to ISO 15016/2015, "Ships and marine technology - Guidelines for the assessment of speed and power performance by analysis of speed trial data", should be consists of the following:

- Evaluation of provided data
- Power correction due to increased resistance due to wind and ripple
- Correction due to seawater temperature and density
- Power correction of the ship speed because of the current
- Ship speed correction due to the effect of shallow water
- Power correction due to displacement
- Presentation of ship performance study results

3.3 EVALUATION CRITERIA

For the purposes of this work, the data sent by two tankers from July 2014 to December 2019 (i.e., for a period of about 5.5 years) were used through the noon reports, as well as the ship performance data. based on sea trials. The two methods used in the present work for the analysis of the case study of a fleet of 2 tankers (see below) are the following:

1. Evolutionary comparison of ship performance based on historical data: The primary goal of monitoring a ship's energy performance is to provide feedback on its performance during a voyage or over a period of time. In this manner, the ship's performance is evaluated not only at the time of measurement, but also over time, depending on the time horizon of the data retained for processing and analysis.
2. Contrast with acceptance tests. The percentage deviation calculated by comparing the daily average speed recorded during the voyage to the theoretically expected value based on the acceptance tests (sea trials) is an indicator of the ship's performance.

Other approaches used in practice to evaluate a ship's performance include comparing its actual consumption with the expected value resulting from various techniques or market-related data, such as shipyard tests, model tank tests, Computational Fluid Dynamics – CFD, and charter parties.

The most common level of reference for assessing a ship's performance is speed/consumption control based on sea trials, data history from previous voyages, and the description agreed in the charter agreement. Specific fuel consumption (SFOC), Maximum combustion pressure (P-max), and Compression pressure (Pcomp) are other appropriate indicators used to evaluate the ship's main engine.

3.4 PROBLEM OVERVIEW

As mentioned before, the purpose of this dissertation is to analyze the factors that affect fuel consumption and to explain any major differences in consumption in a particular route. The research studies a specific route between two ports (port from: SGSIN, port to: AEFJR). This route was followed by two tankers making specific voyages over a period of 5.5 years. During this period, certain differences in the weather conditions per voyage were observed from the data provided. These differences directly affect fuel consumption, and the purpose is to observe the degree to which each of the factors affects the ship's performance. The total data consists of noon reports.

The ships tested are 2 320,000 DWT tankers built in China from Shanghai Shipyard in the period 2014 to 2019.

The data were for 5.5 years and are analyzed in the following paragraphs.

Noon Reports

The noon reports are a report on the condition of the ship that is recorded daily in a data sheet. In earlier years, the data were traditionally recorded, manually at 12.00 noon. Nowadays, data recording is done with the help of measuring instruments. In the ships which were examined, the noon reports include the following information.

- Vessel ID
- Voyage Leg
- Document Date
- Vessel situation (Ballast or Laden)
- Position of the ship received via gps
- Vessel Speed
- Medium axle speed
- Wind Speed
- Swell
- Current
- Trim
- Draft
- Elements of fuel and lubricant consumption

The data, except the meteorological ones, are considered accurate, since they are recorded by meters that have almost zero error. The shaft power has been measured with a flowmeter on the shaft of the machine.

On the contrary, for the meteorological data, values are taken for the situation that prevails during the measurement and that is the area with the highest probability of errors.

Notwithstanding the foregoing, the analysis and processing of measurements relating to the speed, power and speed of the propeller shaft depend on the following factors:

- Vessel situation
  - Hull condition
  - Helix condition
  - Draft
- Weather condition
  - Wind Speed
  - Wind Direction
- Sea condition
  - Swell level
  - Current Speed
  - Current Direction
- Measurement data
  - Measurement accuracy
  - Size of historical data kept

To draw safe conclusions about the ship's performance, all the above factors must be considered, historical data must be kept to the greatest extent possible, and a sea margin must be provided. Furthermore, it is recommended that data be filtered prior to any study in order to remove extreme values or data that do not need to be considered. Sea trials are regarded as reliable and serve as a reference point. The dates of tanking and cleaning of the hull and propeller have been recorded for the time period under consideration.

3.5 FACTORS OF DIRECT DEPENDENCE

Initially, a very important factor in the energy efficiency of a ship is its hydrodynamic properties. To optimize a ship from a hydrodynamic point of view, there are three steps that must be followed:

- Hull optimization
- Propeller optimization
- Hull-helix interaction

The overall resistance of the ship depends on a few components and is a complex problem. In order to study it, it is used to break it down into individual components contained in the final fuel consumption.

❖ *Wind speed*

The true wind speed is the actual speed of the wind as it passes over land or the surface of the sea. Apparent wind is the wind the vessel “feels” as it sails. The apparent wind is calculated as the vector sum of the actual wind and the speed of the ship. Wind force and the direction of the wind will act in increasing or decreasing the load on the Main engine and thus increasing or decreasing the speed of the vessel for the same main engine rpm. if the wind is auxiliary then the ship will not need to develop high speed and therefore power to move. Conversely if it is against the direction then the ship will need to develop more power and consequently consume more fuel.

❖ *Swell*

Swell is the result of the wind blowing on the water’s surface. Wind strength and direction build up a large amount of energy beneath the ocean’s surface forming deeper waves known as swells. Height of each swell is measured from the trough to peak according to the National Oceanic and Atmospheric Administration. Swell direction is the direction the swell is coming from, as opposed to the direction it is heading toward. Sea state is the effect that the local winds have on sea conditions – this is independent of travelling swell waves generated by winds outside of the local area. Sea state is related to the Beaufort scale which describes the state of the sea. The depth of the water also has an impact on swell characteristics. As waves move into shallow water, the waves begin to interact with the seabed. The estimation of the swell's resistance is important for weather routing and performance analysis.

❖ *Ocean current*

Ocean current is a stream made up of horizontal and vertical components of the circulation system of ocean waters that is produced by gravity, wind friction, and water density variation in different parts of the ocean. Sea currents generally affect navigation positively and negatively. They mainly affect it during the lengthening or shortening of the voyage (change of ship speed), the deviation to the left or right of the course and the creation of fog, and secondly, they cause annoying vibrations on the vessel. In case of favorable current, i.e., when the course of the ship coincides or almost coincides with the direction of the current then this results in the ship being swept away by the current in the same direction. This means increasing the speed of the ship and therefore reducing the travel time. Conversely when the course of the current is opposite to the course of the ship the speed of the ship decreases and the travel time increases.

❖ *Propeller*

In conventional ships such as container vessels, bulk cargoes and tankers that sail for long periods of time, fixed pitch propellers are used. A propeller with a larger diameter is more economical at low and medium speeds than corresponding smaller diameters. In addition, a propeller with a larger pitch achieves greater economy at medium speeds. In recent years, the majority of the owners prefer to have propellers on the OPTI DESIGN technique. This technique ensures the best performance with minimal levels of vibration and noise. Thanks to the efficient hydrodynamic blades of the propeller, it reduces operating costs.

❖ *Pollution of the hull and propeller*

More than 6,000 tons of microorganisms can be stored in a VLCC. A small amount of pollution can cause an increase in fuel consumption by 40-50%. By taking in pollution, huge costs can be saved.

❖ *Trim and draft*

Trim is the difference between the draughts forward and aft. The trim of a ship describes its floating position in length direction. It may be by stern or by bow. The draft or draught of a ship's hull is the vertical distance between the waterline and the bottom of the hull. When a vessel is heavily loaded, then it sinks deeper into the water and the draft is getting greater. The trim and draft of the vessel influences the hull resistance and therefore the fuel consumption.

- *Loading condition*

Ballast water is fresh, or saltwater held in the ballast tanks and cargo holds of ships. It is used to provide stability and maneuverability during a voyage when ships are not carrying cargo, not carrying heavy enough cargo, or when more stability is required due to rough seas. For a ship that has no cargo loaded, displacement is less and hence the draft is less. There is less resistance as the lesser surface of the hull is in contact with water and as there is not much load on the main engine, it gives more speed at less power. Whereas for a loaded ship, the draft will be more and thus the resistance against the hull. Also, for the same power of the main engine, the ship will have lesser speed as the load on the main engine will be higher. As a result, weather the vessel is loaded or not, is a factor that affects the speed which affects the fuel consumption.

3.6 SYSTEMS / TOOLS REVIEW

As fuel prices and ship operating costs rise, it is more important than ever for ship owners to reduce energy consumption and improve efficiency. However, for these enhancements to be implemented, performance levels must be evaluated using smart data.

As previously stated, there are numerous factors that influence fuel consumption. They include the current weather conditions, engine performance, maintenance condition, cargo, and so on. Once the data has been collected and measured, it must be properly analyzed in order to be useful to the ship manager. Modern performance management solutions offer services that assist the ship's owner and operator in better managing the ship's performance. The Act-Plan-Do-Check model is used to accomplish this (PDCA Cycle). Performance management can result in efficiency gains of up to 38%.

Figure 4: PDCA Cycle

Source: https://www.qmsuk.com/news/what-is-the-plan-do-check-act-cycle

There are numerous systems available today for evaluating a ship using various approaches. Most previously relied on the noon reports, which are sent daily by the ship's crew to the management company. Modern applications use live data sent by the ship's sensors, resulting in more accurate and reliable data. Furthermore, there are hybrid systems that combine the measurements that have been recorded with the automated data. Finally, weather routing is used by only a few systems. (Looking for a better route) The following are some of the most used monitoring systems:

- LAROS (Lloyd’s Award)

Wireless performance monitoring and analysis system, which allows the analysis of the ship's functions in real time and is connected to any point, regardless of the size or type of vessel.

- CASPER (Propulsion Dynamics)

Analysis of daily logs on board. Periodic reports are sent ashore for additional analysis, after correction for wind and swell conditions.

- KYMA AS

Collection and analysis of real-time data on board.

- DNV GL Eco Insight

- The ECO Insight gate consists of 5 modules that provide a complete performance image of the fleet. Replaces the existing ship-land processes ensuring high quality data.

- Propulsion Analytics

Analyzing routine data collected from ships and comparing it to a custom "digital twin" of the engine can provide performance in any given situation, extract and display important information such as performance indicators, graphs / trends, errors / alerts, capturing the condition of the fleet's engines and providing diagnostics, forecasts, optimization tips, and information for the best ship maintenance planning based on the condition assessment.

3.7 DATA FILTERING

The data for this study came from an excel file provided by the ship's communication platform and the ship's owner. The data was then processed to isolate the main factors that were not required for drawing conclusions. (Discussed in section 3.5) The data isolated and compared fuel consumption for a specific route taken by ships over a 5.5-year period. According to a study, these differences arose as a percentage of existing weather changes, the effects of which are frequently only estimated.

The characteristics of the data that were excluded from the analysis to normalize any extreme values are the following: daily miles, latitude, lubricants, ETA time.

Following data filtering and gap management, the total data volume left to be analyzed was reduced to 76% of the original data volume. This does not imply that the remaining 24% of the data was incorrect; rather, it was more information. They were removed because they added volume to the data rather than something useful that could be used in the conclusions. Following that, a specific voyage (PORT FROM: SGSIN-PORT TO: AEFJR) was isolated during which it was discovered that the available data was sufficient to draw useful conclusions. Furthermore, the specific route was chosen because it occurred 5 times in a 5-year period, making the study's results more accurate. It was the most traveled route of all. For this route, the data taken into account in the study were the following:

- Voyage Leg
- Date
- Wind Speed / Direction
- Swell
- Heading
- Current / Direction
- Trim
- Draft
- Average Speed
- High Sulfur Fuel Oil (HSFO)
- Marine Gasoil (MGO)
- Ultra-Low Sulphur Fuel Oil (ULSMGO)

3.8SAP HANA

The SAP Hana program was used for the study. SAP HANA (High-performance Analytic Appliance) is a multi-model database that stores data in its memory instead of keeping it on a disk. This results in data processing that is magnitudes faster than that of disk-based data systems, allowing for advanced, real-time analytics. Serving as a platform for enterprise resource planning (ERP) software and other business applications, SAP HANA can be placed on-premises, in the cloud, or both, in a hybrid cloud system. The SAP HANA system not only integrates all this data; it can also apply machine learning and AI to analyze it instantly and deeply, accelerating real-time decision-making by providing key insights into a company's operations.

3.9VOYAGES

The data of interest to the study were taken and the fuel consumption for the route studied (SGSIN-AEFJR route) was studied over a period of five years. During these five years, 5 voyages were made on this route. The trips with their dates are listed below:

Table 3: List of voyages studied

Voyage	Voyage No	Date from	Date to	Days
Voyage 1	1092	10/09/2015	24/09/2015	14
Voyage 2	2533	18/04/2018	3/05/2018	15
Voyage 3	3048	24/01/2019	8/02/2019	15
Voyage 4	3152	23/03/2019	9/04/2019	17
Voyage 5	3366	22/07/2019	3/08/2019	13

Source: Author

The average day of each voyage is 14,8 days.

The data for these voyages (weather data and fuel consumption data) were then organized on excel sheets. These sheets were introduced in the SAP HANA program and the statistical presentation of fuel consumption results per day was selected. The results obtained are analyzed in the next chapter.

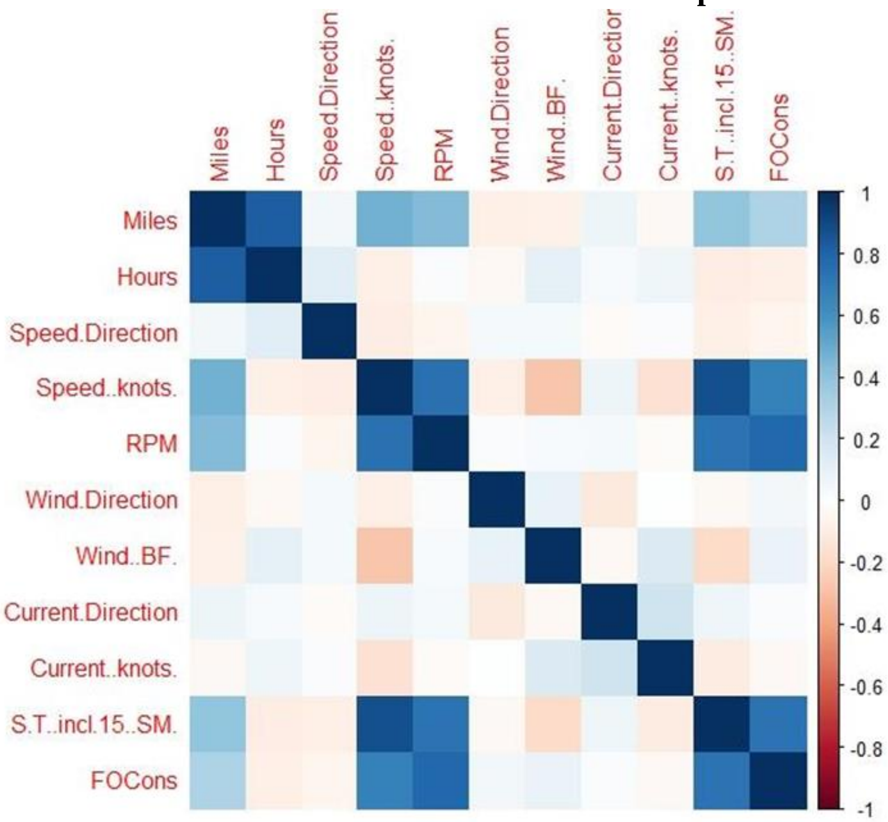
4 RESULTS

4.1 DATA ANALYSIS

With the help of Python programming language and SAP Hana software, some analyzes have been presented that have been presented with statistical graphs. The route chosen is SGSIN-AEFJR and has been studied for 5 different voyages during the 5 years that the data have been given. As shown in the following table, which summarizes the correlations between the variables of the analysis, fuel consumption is mainly related to ship speed and reference data based on sea trials.

It should be noted that in all five voyages the ship is in a ballast situation as it was not found in the data for the specific route laden situation.

Figure 5: Correlation table of variables that affect fuel consumption



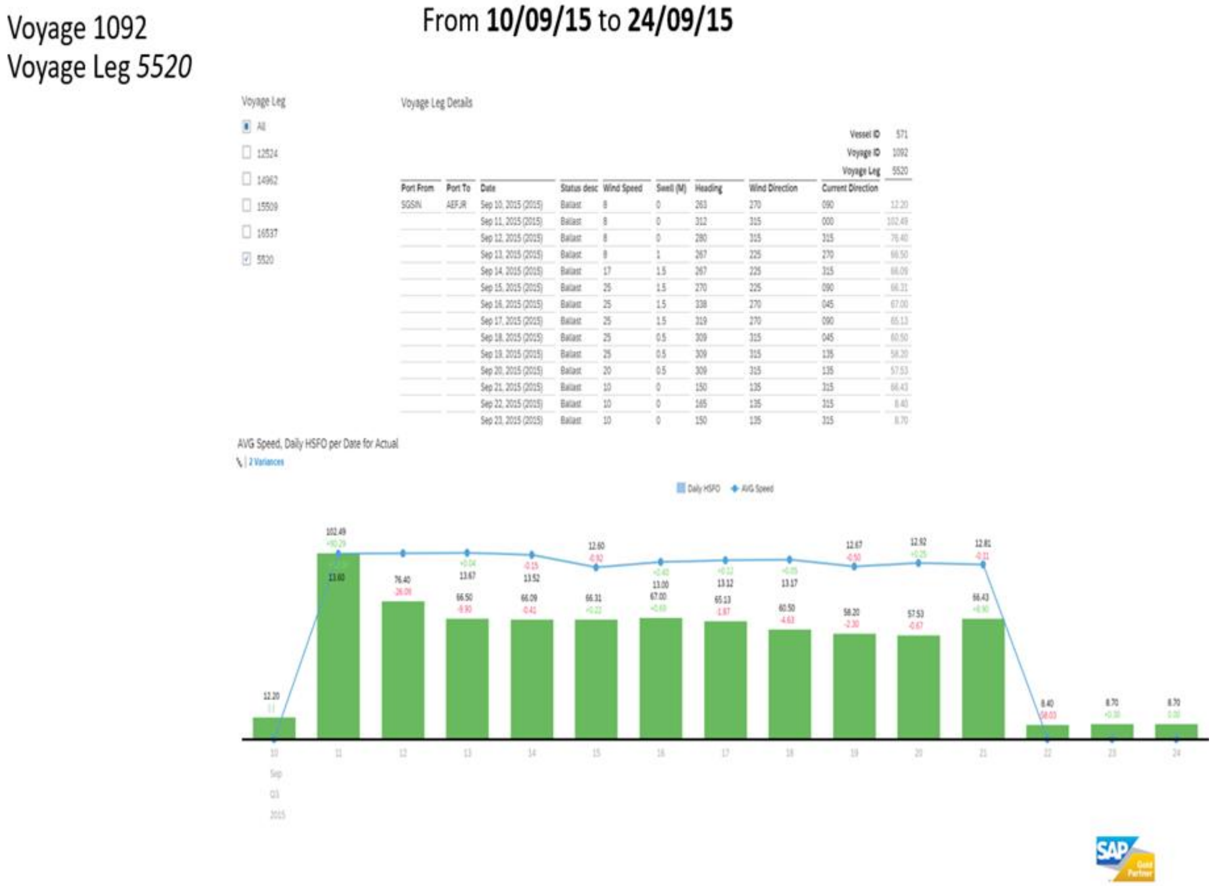
Source: http://www.scielo.org.co/scielo.php

Below, each voyage of this route has been isolated and the fuel consumption analyzed considering the respective weather conditions has been analyzed. The statistical conclusions are presented in bar graphs created with the help of the SAP Hana program.

Voyage 1: Voyage1092 From 10/09/2015to 24/09/2015

The fuel consumption for the voyage 1092 was analyzed, considering the voyage leg 5520. The dates of the voyage were from 10/09/2015 to 24/09/2015 and the ship was in ballast condition. The consumption made by the ship is shown in the following bar chart:

Figure 6: Fuel consumption per day from 10/9/2015 up to 24/09/2015



Port From	Port To	Date	Status desc	Wind Speed	Swell (M)	Heading	Wind Direction	Current Direction	
SGSIN	AEFJR	Sep 10, 2015 (2015)	Ballast	8	0	263	270	090	12.20
		Sep 11, 2015 (2015)	Ballast	8	0	312	315	000	102.49
		Sep 12, 2015 (2015)	Ballast	8	0	280	315	315	76.40
		Sep 13, 2015 (2015)	Ballast	8	1	267	225	270	66.50
		Sep 14, 2015 (2015)	Ballast	17	1.5	267	225	315	66.09
		Sep 15, 2015 (2015)	Ballast	25	1.5	270	225	090	66.31
		Sep 16, 2015 (2015)	Ballast	25	1.5	338	270	045	67.00
		Sep 17, 2015 (2015)	Ballast	25	1.5	319	270	090	65.13
		Sep 18, 2015 (2015)	Ballast	25	0.5	309	315	045	60.50
		Sep 19, 2015 (2015)	Ballast	25	0.5	309	315	135	58.20
		Sep 20, 2015 (2015)	Ballast	20	0.5	309	315	135	57.53
		Sep 21, 2015 (2015)	Ballast	10	0	150	135	315	66.43
		Sep 22, 2015 (2015)	Ballast	10	0	165	135	315	8.40
		Sep 23, 2015 (2015)	Ballast	10	0	150	135	315	8.70

Source: Author

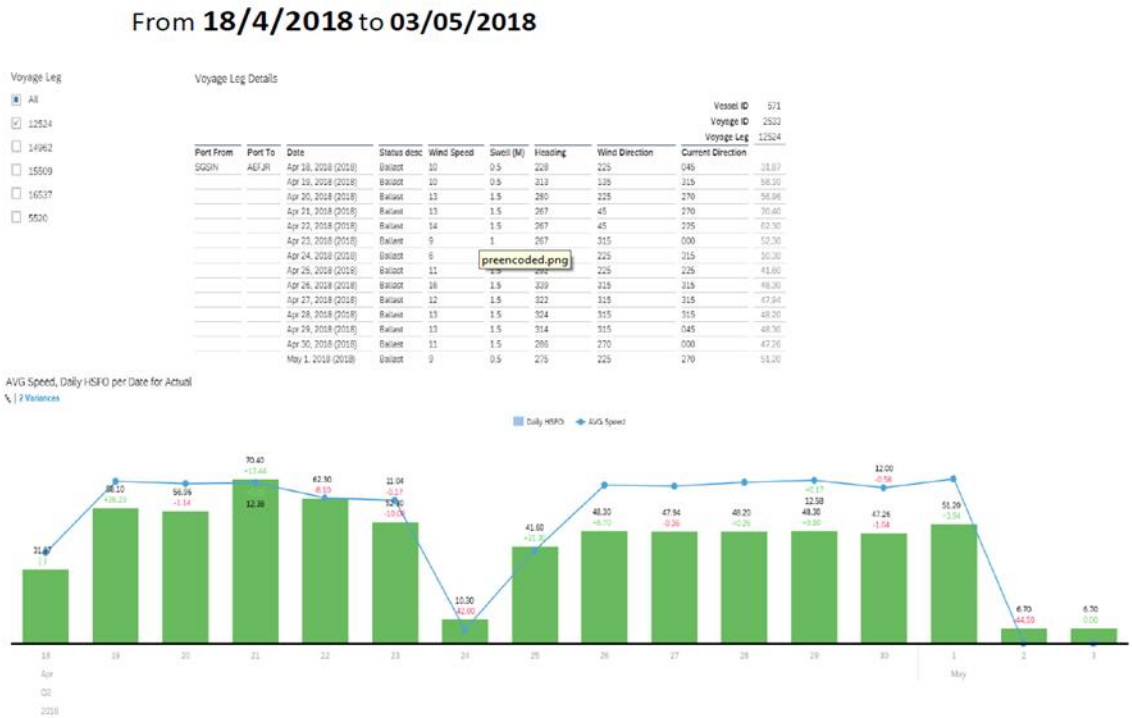
Key Findings:

On 11/09/2015 a significant amount of HSFO was consumed. This could have occurred due to the headwind, which demanded a higher main engine power, in order to reach a desired level of speed. For the rest of the days, HSFO consumption appears to be at the expected levels. Almost zero fuel consumption has been observed in the last three days. This is probably due to the fact that the ship was approaching the port and obviously its speed was reduced considerably and therefore the fuel consumption. This reduction may be due to delays in the port.

<u>Voyage 2: Voyage 2533 18/04/2018-3/05/2018</u>

In this voyage, the voyage leg that has been analyzed is 12524 in which the vessel is in a ballast situation.

Figure 7: Fuel consumption per day from 18/4/2018 up to 3/5/2018



Source: Author

Key Findings:

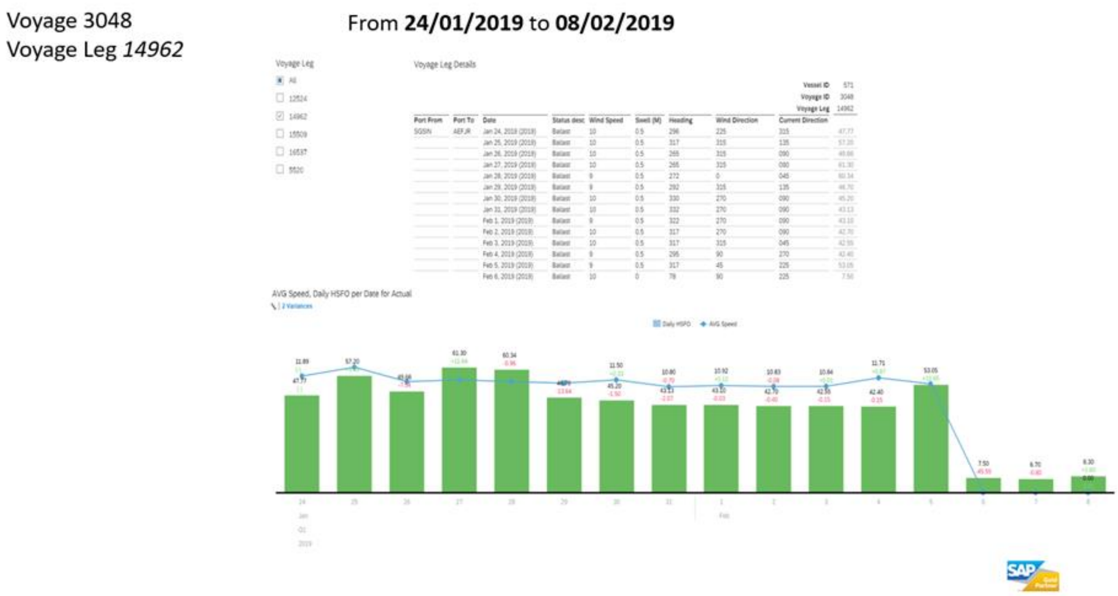
In the first days, in general, there is a constant consumption in the amount of fuel. Obviously, the weather conditions are relatively stable with minimal minor differences due to upstream currents and wind. On 24/04/2018 there is an 80% speed reduction in comparison with 24/04/2018, hence the intense reduction in fuel consumption. On 25/04/2018 the speed seems to be slowly recovered until it is back to a normal level the following day, along with the consumption. This reduction may occur due to the current direction which was not proportional to the course of the ship and as a result the vessel's speed is reduced. This reduction is responsible for the fuel consumption which as observed is lessened. For the rest of the days the speed and therefore the consumption return to stability, about the same as that of the first days.

Consumption remains stable. In recent days there has been a steadily declining consumption due to the same reasons mentioned in voyage 1 in the last days.

Voyage 3: Voyage 3048 from 24/01/2019 to 8/02/2019

The third voyage is analyzed for the 14962-voyage leg and the results are presented on the following chart. The vessel is on a ballast condition.

Figure 8: Fuel consumption per day from 24/01/2019 up to 8/02/2019



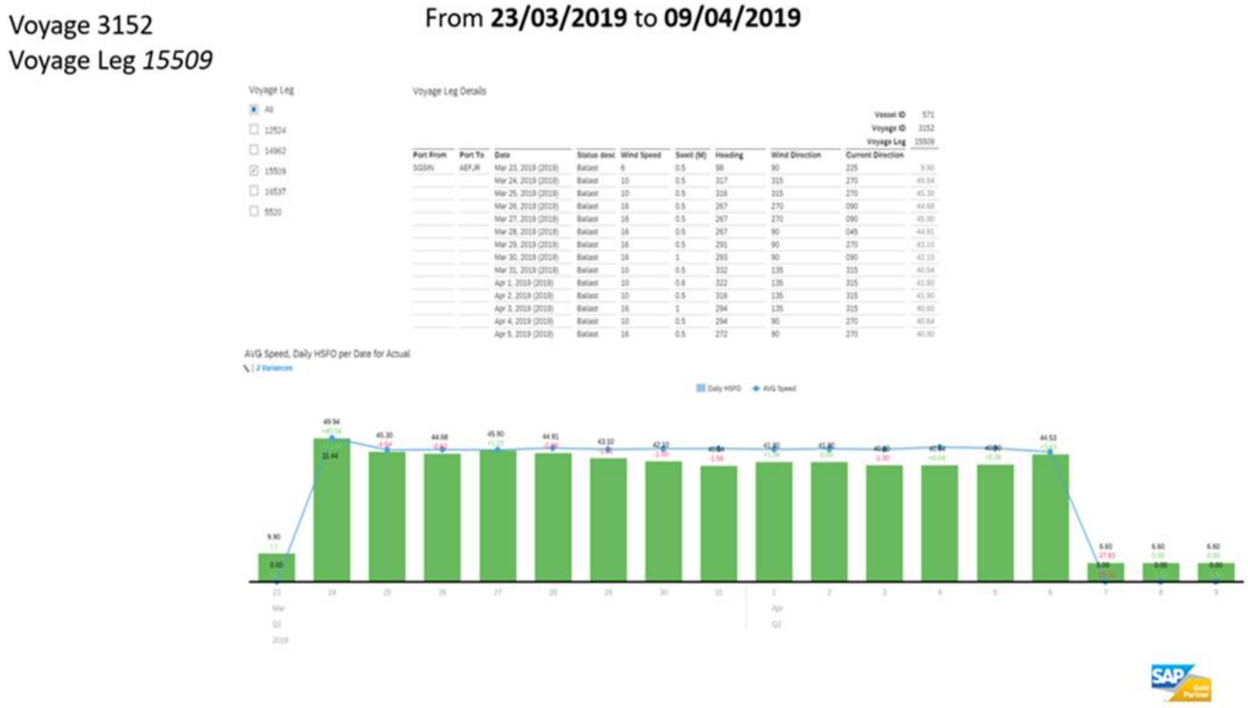
Source: Author

The fuel consumption on the 4th and 5th day of the voyage seems to be higher than expected, according to the vessel's average speed. This may occur because of the direction of the wind that resists the movement of the vessel. Itis therefore observed that a slight difference in weather conditions can change consumption. From 29/01 to 5/02 there is stability in consumption, about the same as that of previous voyages. From 6/02 to 8/02 the ship approaches the port and therefore consumption is significantly reduced.

Voyage 4: Voyage 3152 from 23/03/2019 to 9/04/2019

The voyage leg of the fourth voyage is 15509 and the vessel's situation is ballast. The results are shown in the bar graph below.

Figure 9: Fuel consumption per day from 23/03/2019 up to 9/04/2019



Source: Author

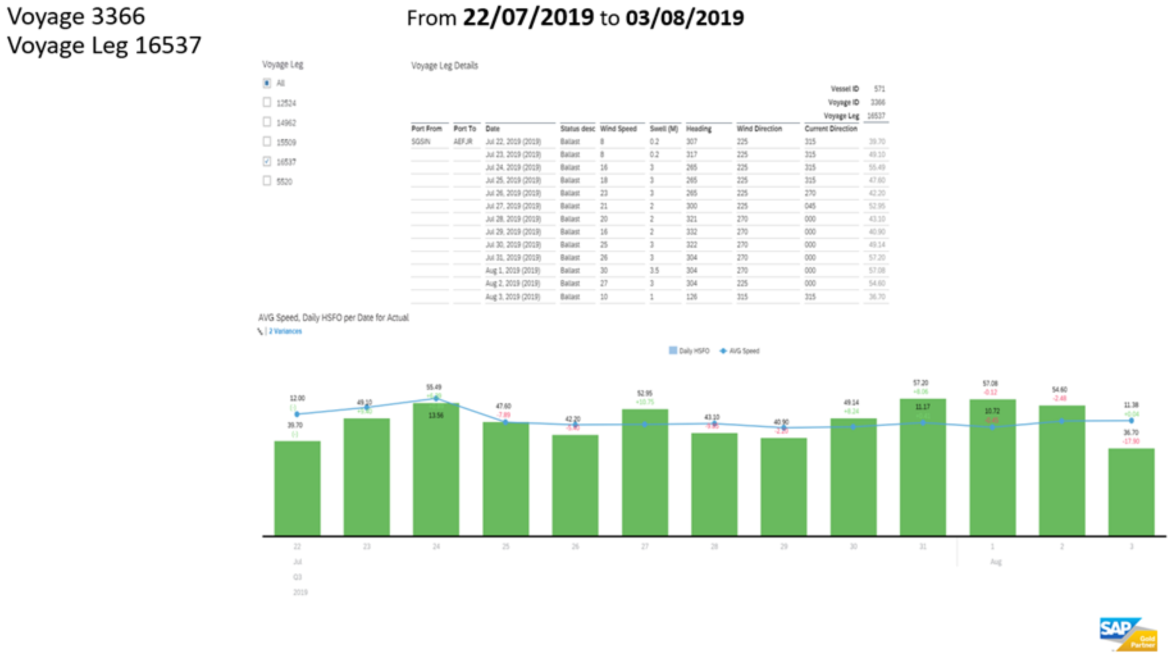
Key Findings:

On this voyage, there is no significant variance in HSFO consumption. The maximum consumption is +10.2% and the minimum is -10.5%. The reason why there is no significant difference is that it is observed that all the factors that affect fuel consumption are at normal levels and therefore the vessel made the corresponding consumption.

<u>Voyage 5: Voyage 3366 from 22/07/2019 to 3/08/2019</u>

The voyage leg that is analyzed is 16537 and its situation is ballast.

Figure 10: Fuel consumption per day from 22/7/2019 up to 3/8/2019



Source: Author

Key Findings:

In general, fuel consumption variations are proportional to those the vessel's speed. Although, on 31/07/2019 & 1/08/2019 the HSFO consumption appears to increase due to the headwind and current. Consumption in this case increases as the wind and the current are not aids to the course of the ship. Therefore, the engine needs to perform more intensively and consume more energy and therefore fuel to respond. The rest of the days the consumption remains stagnant.

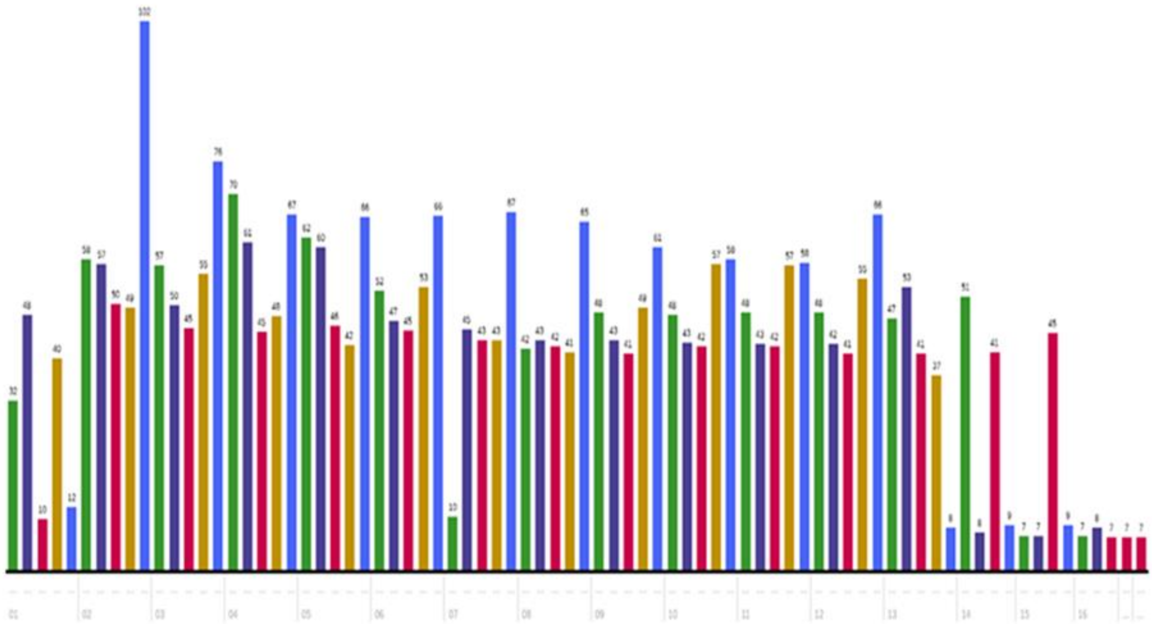
Comparing the different legs:

During voyage leg 5520 a greater amount of HSFO was consumed than every other time this voyage was repeated. This makes sense considering that the average speed of this particular voyage was higher (13,15 knots), while dealing with headwinds that demanded higher main engine power. Due to this fact, the vessel spent fewer days at sea than the other ones.

Voyage legs 12524 and 15509 have identical average speed (10,62 knots). This makes them directly comparable to one another. Same with voyage legs 14962 and 16537, the average speed of which does not significantly differ. (11,36 and 11,42 knots).

In conclusion, it is observed from the voyages studied that the two main factors that affected the fuel consumption to a remarkable degree, are the wind and the sea current. These factors had no auxiliary direction for the vessels, consequently the power of the main engine had to be increased to achieve the desired speed. This led to an increase in fuel consumption. Consequently, it is concluded that wind and current are important factors that directly affect the ship's performance.

Figure 11: Comparison of the different legs



Source: Author

4.2 ASSUMPTIONS

From the presentation of the results, overall, the biggest problems observed in the data collection are the following:

- Discontinuity in the recordings, due to momentary measurements in an ever-changing environment in which the ship is always
- Unreliable recordings, due to error margins in the measuring equipment

- Incorrect entries, due to human error

Also, the following factors, although affecting the performance of the ship, have not been considered because the corresponding data for the needs of the present work were not available.

Water depth: Due to a lack of data on the depth of water in the oceans available via the Internet, calculating the depth of water has become impossible. However, the effect of water depth on the dynamic flow around the hull is thought to be minor, as our measurements concern high-seas cruising, where speed decreases by less than 1% at water depths greater than 100 m.

Characteristics of seawater: Temperature, density, consistency, salinity, pH index, the evaluation of which could provide information on the growth conditions of microorganisms in the hull and propeller of the ship, and therefore, be an indication of ship pollution.

Consumption of auxiliary machines: The consumption of auxiliary electric motors and boilers was not considered in this study, except for the consumption of the ship's main engine, which is the predominant energy consumption when sailing on the high seas.

5 CONCLUSIONS

5.1 CONTRIBUTION AND KEY FINDINGS

The purpose of this thesis is to present the fuel consumption of ships operating a specific route under different weather conditions. Weather directly affects the ship's speed and dynamics and clearly its consumption. Previous research on fuel optimization suggests analyzing using weather data most of them had led to results without including the weather. (Psaraftis andKontovas 2014,Zao 2015).

For the present study, five-year-old data were used for two ships of a large owner company. The data includes the type of ship, route, dates, speed, weather conditions, and fuel consumption. All the above data are presented daily. After the data were properly filtered and a specific route was isolated, the fuel was analyzed daily using the SAP Hana program. The analysis showed some results which were not normal in relation to the rest and deviated from the average. For the specific values (which showed a discrepancy) the respective weather conditions were studied and an attempt was made to explain based on the respective weather phenomena. It was found that a weather condition (e.g., wave, sea current, etc.) can significantly affect the performance of the ship and therefore consumption.The conclusion of the present study is that in order to optimize consumption on a ship, the respective weather conditions should be considered beyond the ship's construction data because they greatly affect performance. Thus, the results can be more accurate, more realistic, and more useful for forecasting. It is important to note that such an analysis is not limited to a research-level for academic reasons. Nowadays the biggest issue for every owner and manager is the ship's fuel because it directly affects the cost and compliance with environmental regulations.

The primary cause of increased fuel consumption could of course be the reduced efficiency of the ship. However, a sensor error, and incorrect or incomplete recordings are critical to the reliability of a ship performance monitoring system. Below are analyzed the benefits and the difficulties that one is called to face during the process of analyzing the energy efficiency of the ship.

Previous studies that have been done on fuel consumption have proven that the weather conditions significantly affect the performance of the ship.(Zhao et al. (2015) ,Qi, and Song (2012), Corradu et al. (2017),Pawel,Defryn and Grigoriev (2020), Bordin and Mo (2019)).However, the specific research has focused not only on the weather factors but on the exact presentation that each one affects the ship efficiency through quantitative representations. The study of a specific route that was followed over a period of 5.5 years by two ships, makes this research more specific and accurate. This happens because the more the sample that is studied under specific conditions, the more reliable the results. The representation of the results in bar graphs displaying daily fuel consumption allows for a more accurate indication a better understanding

5.2 MOTIVATIONS AND CHALLENGES

The benefits of monitoring a ship's energy efficiency, in addition to the obvious cost savings, are summarized below.

Environmental benefits

The global challenge of addressing climate change, the rising cost of operating a ship, and new international shipping regulations are the primary factors that necessitate monitoring the ship's energy efficiency. The greater the complexity of the legal framework governing the Shipping sector and the greater the demands of charterers, the greater the volume of large-scale data that must be carefully considered and analyzed to draw safe conclusions about the ship's performance.

Assessment of the condition of the hull

The collection, processing, and analysis of fuel consumption data during ship operation can be used to make informed decisions about the need for hull cleaning, the quality of anti-pollution systems, or the interval between two tanks.

Assessment of the condition of the machine

Continuous monitoring of fuel consumption can reveal issues related to the main engine's decreased efficiency, allowing for proper adjustment and maintenance work. It also allows for the proper scheduling of technical work on the main engine and auxiliary systems, such as valve, piston, and air filter changes.

Increased competitiveness

Guarantees regarding fuel consumption and speed levels provided under charter agreements are frequently inaccurate because it is unknown whether a ship's poor performance is due to difficult weather conditions or poor ship maintenance. When, on the other hand, a ship's performance is known, controlled throughout its life, and clearly defined regardless of external environmental or loading conditions, the shipowner gains a competitive advantage in concluding charter agreements.

Performance optimization

If all of the parameters that affect the ship's performance are recorded and checked on a regular basis, a large database can be created that can be used to properly configure many parameters throughout the ship's life. Furthermore, with optimal maintenance frequency and quality, the wear of the electromechanical systems and the hull will be slower. Finally, the availability of reliable information on the ship's performance enables the crew to gain a better and more immediate understanding of the effects of their actions on the ship's performance. It can also be used to find the best navigation route and the best loading conditions. Monitoring and constantly monitoring the ship's energy performance, on the other hand, is a difficult task. The following issues arise when investigating a ship's energy efficiency using noon reports:

- Data reliability

One of the biggest challenges encountered in analyzing large-scale ship performance data is the reliability and consistency of this data. In order to improve the reliability of the data coming from the noon reports, it is necessary to filter them. Automated extraction and storage of related parameters is the only way to overcome this difficulty.

- Meteorological data

Also, the values related to the weather data recorded have a high degree of uncertainty, as they related to the state of wind and sea currents at the time of measurement, with the result that, in case of strong fluctuations in prices, they cannot be estimated correctly. An important factor in this parameter is, in general, the insufficient training of the crew on the performance of the ship, e.g., observations of the swell.

The issues are addressed in the scientific discipline of machine learning, which encompasses a variety of algorithms that may be trained using massive volumes of data (big data) to tackle prediction, classification, and decision-making problems. The main distinction between them and traditional systems is that their operating principles are derived from the facts themselves, rather than being set by programming rules or mathematical models.One of the most significant benefits of machine learning applications is that they can frequently discover new, unfamiliar rules to solve a problem, as well as the relationships that may exist between the data, and use them to find a solution to a problem that could not be found using a theoretical approach. In addition, as fresh data is received, the algorithm can be re-trained and learn from its mistakes, improving its performance over time. Below are the advantages and disadvantages of the classical approaches compared to the machine learning methods.

Advantages of noon reports

Low equipment maintenance requirements, Applicability to smaller data sets, no long time required for data collection and analysis, The result of the analysis is easy to understand.

Advantages of live data

High measurement frequency (high accuracy), Almost zero human intervention, Continuation of measurements and recordings, no prior knowledge required to apply the algorithms.

Disadvantages of noon reports

Low frequency of measurements (24-hour average), High probability of error due to human factor (when reading, measuring, recording), Discontinuity of recordings.

Disadvantages of live data

High equipment maintenance requirements, A large amount of heterogeneous data is required to be adequately trained, Only the solution of the problem is shown and not its logic, so that it cannot be adequately justified.

In conclusion, the findings of this study highlight the need of controlling and monitoring the ship's energy efficiency. Only fuel consumption accounts for around 60% of a ship's overall running costs, depending on the kind and operation of the ship, with the other 40% of operating costs going to the crew, port costs, and ship maintenance and repair.As a result, it is evident that the figures, both in terms of the amount of fuel burned and the amount of financial cost involved, imply that continuous monitoring and analysis of large-scale data will result in huge global savings in both available energy resources and financial expenditures.

5.3 FUTURE RESEARCH

Starting with the current study, further research directions are recommended in the final chapter of the work. This paper looked at the issue of a ship's energy efficiency from both a theoretical and practical standpoint to paint a realistic picture of the problem of fuel conservation in ships. Thus, the interdependencies are confirmed and the problems that one must face are highlighted through the synthesis of theoretical study and practical application of statistical analysis methods in real data, thus setting the specifications for further analysis of the factors that affect a vessel's fuel consumption.

The most important expansion of this research is the calculation of the environmental benefit from fuel savings as well as the environmental costs of inaction. The greenhouse effect, the adequacy of traditional energy resources, and climate change are all worldwide issues; hence the environmental benefit dimension is global. It’s worth mentioning that while there is a definite link between energy and CO_2 emissions, the two ideas should never be confused. The Energy Efficiency Operational Indicator (EEOI) and the Energy Efficiency Design Index (EEDI) would be equal to zero if a ship was propelled by battery-powered electric motors and operated with "clean" electricity and zero CO_2 emissions. Of course, this does not negate the ship's energy use. In fact, totally "electric" ships weigh heavier than diesel ships since the requirements for electric batteries account for a significant portion of the ship's total weight, consuming more energy. Machine learning methods could also be used in future work to use real-time data (live data) obtained from automated monitoring systems, with a greater depth of time and for a larger number of ships. One of the most significant advantages of machine learning approaches is that having a large amount of good data is frequently more important than having strong algorithms. However, as previously said, adequate training requires a large amount of diverse data.

In this regard, the methodology used in this study might be applied to cases of installing energy-saving technologies to assess their efficacy by comparing the ship's performance before and after their installation.

Another angle that emerges from this research is the investigation of the relationship between ship design and fuel use. A ship's energy efficiency is mostly determined by its design and management. The elements that affect a ship's fuel usage during operation, rather than its design, are investigated in this study.

Finally, this research could be expanded to investigate the interdependence of additional aspects in fuel usage. Unlike many other ship performance measures that deal with fuel use, lubricant usage is visible in the shipowner's account, and shipowners will reap the benefits of the savings. The advantages include immediate lubrication savings as well as reduced engine maintenance requirements. Other factors that could be investigated, assuming the necessary data is available, include seawater temperature, salinity, the type and category of anti-pollution systems and reef paints, ripple height, hull cleaning quality, and so on. These are all inextricably linked to the ship's resistance and, as a result, to the final fuel consumption. As a result, more research into these issues could lead to useful conclusions about how to improve the ship's energy efficiency, with all the associated economic, operational, and environmental benefits.

BIBLIOGRAPHY

- T. W. F. Hasselaar, An investigation into the development of an advanced ship performance monitoring and analysis system, Newcastle upon Tyne, UK: Newcastle University, 2010
- S. F. Soren Hansen, An Integrated Vessel Performance System for Environmental Compliance, Springer International Publishing, 2018
- B. L. C. G. Eric Hagestuen, Continuous Performance Monitoring - A Practical Approach to the ISO 19030 Standard
- Anti-fouling systems, IMO, 2002.
- K. Lauri, Study of Hull Fouling on cruise vessels across various seas, Helsinki, Finland: ENIRAM, 2012.

- W. Y. W. W. T. S. K. C. W. Y. Feiyang Zhao, «An Overall Ship Propulsion Model for Fuel Efficiency Study, » The 7th International Conference on Applied Energy - ICAE2015, 2015
- B. M. L. A. K. P. C. J. J. O. S. Lokukaluge P. Perera, «Evaluations on ship performance under varying operational conditions, » ASME 2015 34th International Conference on Ocean, Offshore and Arctic Engineering, 2015
- P. Dynamics. Available: https://www.propulsiondynamics.com/.
- «BMT SMART, » Available: http://www.bmtsmart.com
- IMO, Third IMO GHG Study, London: International Maritime Organization, 2014.
- T. S. (. Lefteris Karaminas, Ship powering performance - Learning from the challenges faced by Owners, London, UK: The Royal Institution of Naval Architects, 2016.
- C. G. Bjarte Lund, «The Big Data Concept in a performance monitoring perspective, » 2017.
- ISO 15016/2015, “Ships and marine technology – Guidelines for the assessment of speed and power performance by analysis of speed trial data”.
- S. Harvald, Resistance and Propulsion of Ships, New York: John Wiley & Sons, 1983.
- B. M. Lokukaluge P. Perera, Ship speed power performance under relative wind profiles, Trondheim, Norway: Norwegian Marine Technology Research Institute (MARINTEK), 2016.
- «Energy matters to climate change, » 2018. Available: https://www.e-mc2.gr/.
- «KYMA, » Available: https://www.kyma.no/.
- «Laros, » Available: http://www.laros.gr/index.php/laros.
- Study on the optimization of energy consumption as part of implementation of a Ship Energy Efficiency Management Plan (SEEMP), London: IMO, 2016.
- I. P. o. C. C. (IPCC), «Assessment Report (AR5), » 2014. Available: https://www.ipcc.ch/.