IMPLEMENTING PREDICTIVE MAINTENANCE IN MARITIME OPERATIONS: A CASE STUDY WITH FRUGAL TECHNOLOGIES

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ABSTRACT

The growth of technology and sensory data increases the possibilities for the maritime sector to adopt predictive maintenance solutions and become more efficient in terms of asset management. This study was conducted to contribute to the development of a predictive maintenance solution being developed by an innovative company in the marine industry. By this case study, meteorological effects were studied over vessel performance, specifically in fuel consumption and shaft power values. These values are used to calculate the specific fuel oil consumption (SFOC) indicator, which is the engine KPI guiding the current PdM solution. Different engine behaviours are identified over different weather situations, allowing to recreate the ideal fuel consumption curve in near-calm water sailing conditions. Additionally, a ML model is trained and tested, serving as a predictive tool for extra fuel usage due to weather loads. With this, the values for the SFOC can be recalculated and is a step forward in the overall PdM solution.

CONTENTS

LIST OF ABBREVIATIONS

Abbreviation	Full Form or Meaning
AI	Artificial Intelligence
ANN	Artificial Neural Network
CBM	Condition Based Maintenance
CFD	Computational Fluid Dynamics
CM	Condition Monitoring
CRISP-DM	Cross Industry Standard Process for Data Mining
DL	Deep Learning
FOC	Fuel Oil Consumption
IMO	International Maritime Organization
IoT	Internet of Things
MAE	Mean Absolute Error
ML	Machine Learning
MRV	Monitoring, Reporting and Verification
PdM	Predictive Maintenance
PLS	Partial Least Squares
PvM	Preventive Maintenance
R2F	Run-to-failure
SFOC	Specific Fuel Oil Consumption
SQL	Structured Query Language
SVM	Support Vector Machine
TBM	Time Based Maintenance

1. Introduction

Most worldwide goods and products are transported by ocean freight, making marine transportation the pillar of the globe's economy. Approximately 80% of global trade is made by sea, and more than 90.000 ships sail in the ocean daily (Karatuğ & Arslanoğlu, 2022). Accordingly, it becomes crucial to manage vessels efficiently and to adopt sustainable strategies. In recent years, the International Maritime Organization (IMO) has implemented new regulations that aim to reduce global cargo emissions by 50% by 2050, in comparison to 2008 levels (*International Maritime Organization. 2024*).

With the advent of Industry 4.0, a wide range of areas in the industry are incorporating the use of computers and digitalization, and maintenance is one of them (Abidi et al., 2022). Recently, predictive maintenance (PdM) has become increasingly important, serving as a guiding tool to increase equipment utilisation, reduce downtime, avoid unnecessary maintenance and estimate remaining lifetime (Jimenez et al., 2020). The main objective of PdM is to anticipate potential failures and subsequent deterioration, and optimising the maintenance on marine vessels is one of the most important ways to improve reliability and sustainability of the machinery (Karatuğ & Arslanoğlu, 2022). A well designed maintenance strategy is one of the effective approaches to the end goal of energy efficient operations in marine vessels, with fewer emissions released into the atmosphere (Karatuğ et al., 2023a).

Though the industry is still predominantly reliant on a time-based, prescriptive approach to maintenance, there are a number of factors challenging the long-held norm (Lazakis et al., 2018). The increasing complexity of shipboard systems and the growth of smart ship concepts, data-driven solutions and Artificial Intelligence (AI), create a promising path for transforming the maritime landscape (Karatuğ & Arslanoğlu, 2022). Leveraging the power of data, stakeholders in the maritime sector reveal new opportunities to optimise operations, enhance safety, and drive sustainability initiatives (Aydin & Guldamlasioglu, 2017).

The actual project is a part of an ongoing predictive maintenance solution related to vessel engines, which a company from the industry is currently developing. Such a solution requires substantial domain expertise and quite a large amount of collected data to facilitate the implementation of machine learning algorithms. At its core, the whole big project is based on the use of the Specific Fuel Oil Consumption (SFOC) engine efficiency indicator as the fundamental to analyse engine degradation over time. However, the reliability of this indicator is compromised -or noised- by external factors such as hull condition, that leads to an extra shaft power due to resistance, propeller fouling, which requires extra shaft power due to a worse propeller condition and weather variations, which also requires extra shaft power due to severe winds and waves. Hull condition and propeller fouling effects have already been solved by the company in collaboration for this project, leaving for analysis an influential factor on this SFOC indicator: the effect of the weather.

Thereby, the actual project is focused on understanding how weather loads influence the shaft power and fuel consumption in a vessel, which are the two main variables used to calculate the SFOC. The end solution will present a machine learning (ML) model that, trained on a large amount of data where a feature of fuel over consumption has been calculated, will be able to inform the ship owners at a specific point in time how much extra fuel they are using for specific sailing conditions, accounting for external weather factors. The main logic behind this data-driven project will be the recreation of “perfect” or “calmed” sailing, in order to use it as reference when the weather gets rough and intense.

Sailing in adverse weather conditions can increase fuel consumption and CO_2 emissions by over 50%, and Fuel Oil Consumption (FOC) constitutes approximately two-thirds of a vessel’s voyage costs (Gkerekos & Lazakis, 2020). Hence, identifying the relationship between weather and vessel data can yield to make more informed decisions, and constitute the pillar for a more complex solution, such as a weather routing or voyage optimization system.

This project is aligned with both the contribution to a big ongoing project for Frugal - PdM - and the creation of a practical ML solution. The research question that instigates the problem is:

- *Research question - What is the influence of meteorological conditions in the performance of a vessel based on a data-driven and ML approach?*

The factors, contributing to the current PdM solution, are associated with the engine shaft power and fuel consumption. Hence, the influence of the weather is studied from the perspective of these two variables, deriving a more specific sub question:

- *Sub question - How are the shaft power and fuel consumption variables influenced by weather loads?*

Addressing both questions would constitute a step forward in the solution that the company is developing, as well as opening new opportunities for more enhanced solutions and additional value to their product. On one hand, it addresses weather effects on the variables pertinent to the SFOC indicator, and in this vein, it combines vessel and meteorological data and explores for potential decision making applications.

The project will be structured in the following way: chapter 2 firstly introduces the case study and the company. Chapter 3 introduces the CRISP-DM, a data science methodology: Business Understanding, Data understanding, Data preparation, Modelling, Evaluation and Deployment are the main procedures of the work frame. Each of the sections are explained in how they have been applied throughout the project. Furthermore, this chapter explores how the methodology is combined with an Agile philosophy, which helped in not missing any aspect of the project and allowed going back and forth when necessary. Chapter 4 emphasises in an overview of traditional maintenance strategies, as well as it provides a list of advantages when comparing modern maintenance against traditional ones in the industry. This chapter also explores the relevance of meteorological effects in vessel performance, known as seakeeping, providing details on factors such as winds and waves and how they affect ships during sailing. It explains and compares physics vs data based approaches. Moreover, this chapter tracks the evolution of research articles within this domain, which served as inspiration for the current developed solution. Chapter 5, 6, and 7 contain the technical development of the idea where the initial research question and sub question are discussed, along with a summary of key findings, limitations and future work.

2. Case study

Frugal Technologies, created in 2017 and based in Aalborg, is formed by professionals from both the marine and software industries. These professionals develop modern software that helps marine logistic companies improve their operations through the use of technology, data and AI solutions. Among different ongoing projects, Frugal Technologies is currently developing a predictive maintenance solution that will not only help their customers in taking more informed decisions about their assets in terms of maintenance, but also contribute to a healthier environment by the reduction of CO_2 emissions and spare parts over waste.

Frugal Technologies collects data from more than 50 vessels daily, opening the possibilities to learn, practice and ideate different solutions with the combination of analytical tools and data leverage. Moreover, this collaboration links academic learnings with real world needs and problems, creating a very enriching experience. This project constitutes the last semester of my MSc in Business Data Science, and throughout the process, I have had the possibility to work everyday at the Frugal Technologies offices in Aalborg, having my own space, access to a vast amount of data and most importantly, having the help of my amazing colleagues.

3. Methodology

With its systematic procedures, CRISP-DM is a renowned methodology in the field of data science, offering a clear roadmap to navigate the complexities of data mining projects. Being a step-by-step guide, from business understanding until the final deployment, every aspect of the project is carefully covered (Schröer et al., 2021). Data mining is a creative process which requires a number of different skills and knowledge, and the success of such a project relies on the proper mix of good tools and skilled analysts (Wirth & Hipp, 2000). Under the umbrella of data science projects, CRISP-DM is the methodology which has become most popular since it was published in 1999 (Hotz, 2024).

In this project, the methodology has been applied in combination with an agile approach, where moving back and forth at different stages has been essential. Understanding vessel engine data hasn’t been a straight line, and the help of personnel from the company was necessary to counterweight the lack of technical knowledge in many aspects. Therefore, the CRISP-DM model gives a set of necessary steps and recommendations in order to successfully carry out the data mining cycle (See Fig 1).

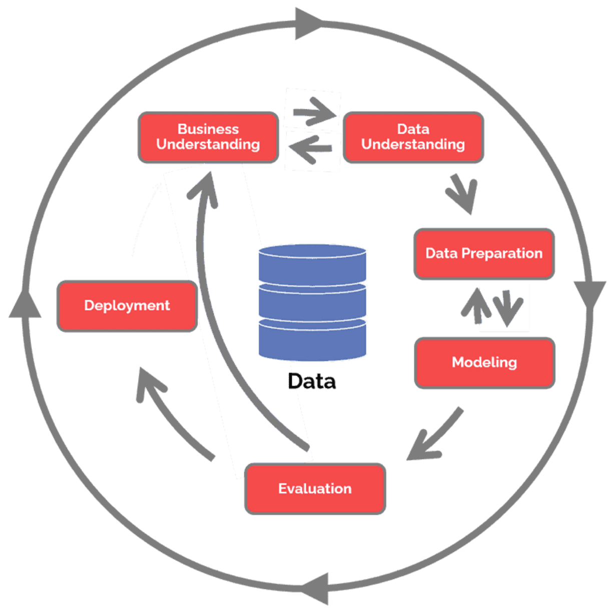

Fig 1 - CRISP-DM. Extracted from (Hotz, 2024)

Each stage of the CRISP-DM process will be presented below, and explained to how it was applied in the context of the proposed ML solution during the development of the project.

3.1 Business understanding

The initial phase focuses on understanding the project objectives and requirements from a business perspective, and then converting this knowledge into a data mining problem (Wirth & Hipp, 2000). This phase involves collaborating closely with stakeholders and carefully analysing how the actual product can be improved by the use and exploitation of data (Hotz, 2024).

In the case of this project, the overarching goal was the contribution to an ongoing big project being developed by the company. However, due to the given timeframe and the limitation in domain expertise (marine engineering), the definition of the goals and planning required a lot of teamwork and communication. Since a lot of data and opportunities were at hand, we had to find a realistic solution that was doable with the above limitations.

Incorporating the weather data combined with vessel operational data surged as the best option after analysing different scenarios, and this approach would enhance the actual product of the company and add new value.

By leveraging historical data on weather conditions and corresponding vessel behaviour, the idea leaned on developing a data based approach that could represent how weather affects two specific parameters of the vessel: shaft power and fuel consumption.

After this process of discussing how the data could be leveraged and aligned with business goals, the objectives were translated to the form of a problem statement, and served as guidance throughout the development of the whole project and more importantly, assured that the solution proposed pointed in the right direction.

3.2 Data understanding

The data understanding phase begins with an initial data collection and continues with actions in order to get familiar with the available data, to identify data quality problems, or to discover first insights into the data (Wirth & Hipp, 2000). According to CRISP-DM, four steps must be followed: collect initial data, describe the data, explore the data and verify data quality (Hotz, 2024).

A large amount of data was available at the beginning, and the collaboration of the colleagues from the company made possible the selection of the most pertinent features. This collaborative approach brought different knowledge, points of views and perspectives. For the current project, it was decided to look at one vessel's data in order to scale down the task, and improve it one step at a time. This decision was also made in order to simplify problems of data misalignments corresponding to different vessels and sensors.

3.3 Data preparation

The data preparation step consists of all the activities focused on preparing the final dataset. This data will be fed into the model and it is usually cleaned out of anomalies, preprocessed and included with new features. Data preparation tasks are likely to be performed multiple times, and not in any prescribed order (Wirth & Hipp, 2000). A common rule of thumb is that 80% of the project is data preparation. Indeed, it consumed a lot of time in this project. The five tasks to be performed are: select the data (determine the datasets that are gonna be used), clean the data (null values, duplicated values or any inconsistencies), construct the data (add new features if necessary, feature engineering), integrate data (combine data frames) and format data (reformat data types if necessary, dummies for example) (Hotz, 2024).

Each dataset selected for this project (weather and vessel data) went through cleaning practices to address null values, redundant entries, and inconsistencies, making possible that the data was reliable. After the cleaning, the datasets were integrated, and the relevant information from both sources was stored into a single cohesive dataset. During next steps, new features were added to improve the dataset's richness and provide valuable insights for further analysis. Upon this, the logic for the final ML model was built based on visualisations that provided a better understanding of the ship speed power performance.

Even though preparing the data consumed a significant amount of time and effort it was a valuable learning process. Later in the report, a more comprehensive explanation of these preparation tasks is presented, detailing the specific methods and techniques employed.

3.4 Modelling

In this phase, various modelling techniques are selected and applied, and their parameters might be calibrated to obtain better results or predictions (Wirth & Hipp, 2000). This phase is widely regarded as data science’s most exciting work and often the shortest phase of the project. The 4 steps recommended are: 1) Select modelling techniques, determine which algorithms to try (e.g. regression, neural net). 2) Split the data into training and validation sets. 3) Build the model, and 4) Asses models. Generally, multiple models are competing against each other, and the data scientist needs to interpret the model results based on domain knowledge, the pre-defined success criteria, and the test design (Hotz, 2024).

In this project, a regression model was created and showed satisfactory performance. The main function of the model is to estimate the additional fuel consumption that a ship may experience due to weather loads. A ship speed power performance analysis was carried out to determine the engine behaviour or operating zones over different climate scenarios. This comprehensive approach enabled the development of a model capable of offering insights into the influence of weather on maritime operations.

3.5 Evaluation

The evaluation phase consists of reviewing the model not from a technical but rather from a business perspective. Before proceeding to a final deployment of the model, it is important to review the steps executed to construct the model, to be sure it properly achieves the business objectives (Wirth & Hipp, 2000). The steps are: 1) Evaluate results, do the models meet the business success criteria? Which one(s) should we approve for the business? 2) Review process, review the work accomplished. Was anything overlooked? Were all steps properly executed? 3) Determine next steps, based on the previous three tasks, determine whether to proceed to deployment, iterate further, or initiate new projects (Hotz, 2024).

For the evaluation of the actual process, the project didn't follow a linear path and required several iterations, but it can be said that all relevant business aspects were considered and addressed. The main goal, based on quantifying the effect of the weather using a data driven approach, was accomplished. Indeed, the model's performance was tested using historical data with a train-test split, ensuring its robustness and effectiveness in real-world scenarios.

In regards to future steps, the project has the potential to serve as a foundation for an enhanced solution. Nevertheless, refining the model's logic to achieve better results would demand additional time and expertise, and it's a consideration that the company should study carefully.

3.6 Deployment

During the last phase of the CRISP-DM the focus changes to apply the ML model to a real environment. This would involve integrating it to real operations, infrastructures and systems. The four main tasks are: plan deployment, plan monitoring and maintenance, produce final report and review the project (Hotz, 2024).

Nevertheless, throughout the creation of this project the previously mentioned deployment phase couldn't be implemented entirely. This was caused by time limitations and priorities. Instead, Streamlit was used to develop a simulation interface, a tool to create interactive data web applications. Streamlit serves to show the capacities of the model and discuss with stakeholders the potential of the solution, since it can show real time predictions and visualisations.

4. Literature review

Maintenance cost in industry and process plants is a major share of the total operating cost of all production. For any specific type of industry, these costs can be around 15%-60% of the cost of products produced (Motaghare et al., 2018). Predictive maintenance has emerged as a promising approach to optimise asset management and reduce operational costs in various industries, including the maritime sector. Vessel maintenance tasks affect the reliability and levels of the shipping industry and are important factors in the lifecycle of a ship, they can minimise down-time and reduce operating costs as it accounts from 20%-30% of the ship's overall operational expenses. The advocates of change mention that a move from scheduled, rule-based maintenance to a data-driven, risk-based approach can lead to more accurate and timely maintenance, decreasing costs and increasing availability of ships systems and safety (Lazakis et al., 2018).

In the field of research, according to (Carvalho et al., 2019), who made a systematic literature review for machine learning methods for predictive maintenance in industry (concretely in machinery and production plants), the number of articles published at databases such as IEEE Xplore and ScienceDirect between 2009 and 2018 has increased exponentially. Before 2013, only two papers were published. But after that, it increased significantly. The average number of papers went up from just half a paper per year between 2009 and 2012 to a number of 11.3 papers per year from 2013 to 2018. They suggest this finding as the notion that PdM is becoming more important with the development of technology and the increase in the amount of data generated by industrial equipment. Nevertheless, although the trend line is increasing, the amount of articles published can be considered small due to the complexity of implementing efficient PdM strategies in production environments. This complexity is related to two key needs: domain expertise in the areas of ML/data-science and previously run-to-failure (R2F) or preventive maintenance (PvM) strategies to generate historical data (Carvalho et al., 2019).

Hence, if looking at LENS.ORG, which is an open resource database where its possible to find and analyse scholarly data, it's possible to see from Fig 1 that the count of scholarly works within the domain of predictive maintenance in industry and machine learning has increased from around 100 articles in 2009 until almost 1000 in 2024. This database accounts for not only IEEE Xplore and ScienceDirect scientific literature and provides a broader picture of the paradigm.

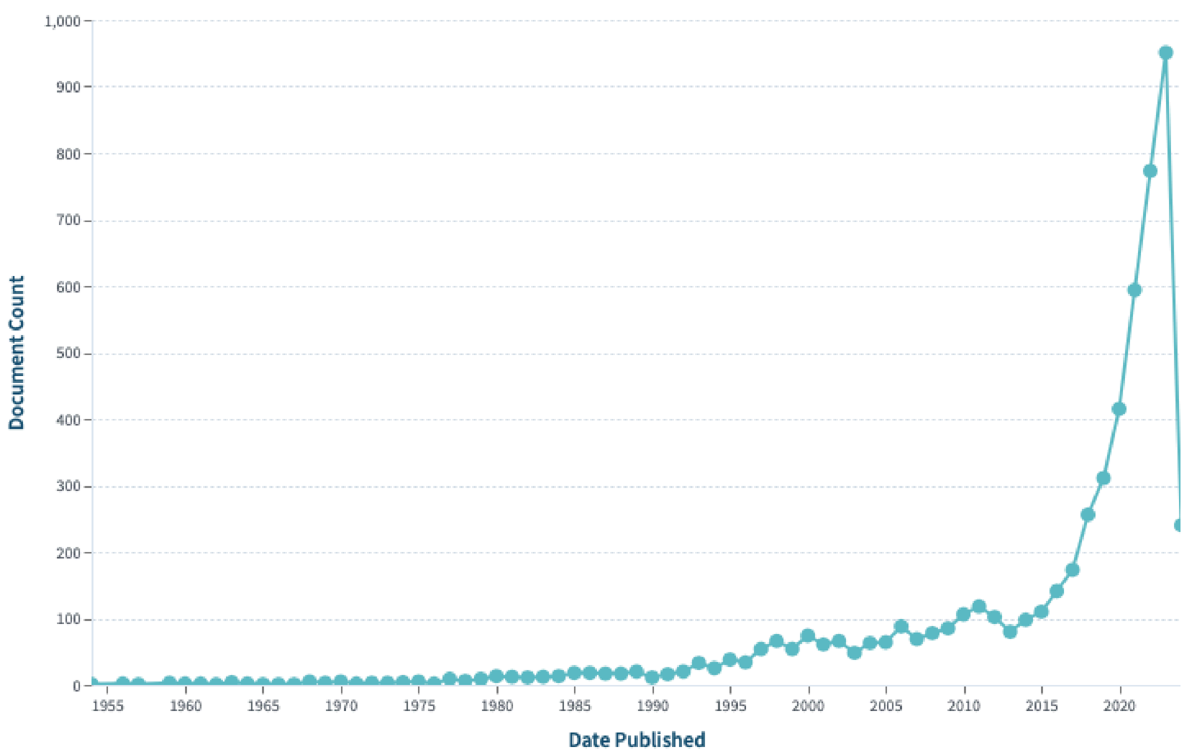

Fig 2 - Scholarly works over time in Predictive Maintenance in Industry Machine Learning, from LENS.ORG

4.1 Overview of maintenance strategies

In literature, different maintenance nomenclatures can be found, but the typically employed maintenance strategies are: run-to-failure, also known as corrective maintenance, preventive maintenance and predictive maintenance (Carvalho et al., 2019).

- R2F is a technique where no maintenance actions are done or scheduled to be done, unless and until any equipment or system failure occurs. In this maintenance strategy, even if small errors are identified, no maintenance is done until the whole system breaks down and stops working. It may include some precautionary tasks such as lubrication or adjustments but no major repairs are done before the system fails to operate (Motaghare et al., 2018). Generally speaking, following this strategy is not considered an effective approach for businesses, as they are forced to react to situations rather than planning and anticipating in advance. However, this type of maintenance strategy is not always completely wrong, and it can be accepted if failure of current equipment does not affect regular operations and the organisation's overarching goals (Jimenez et al., 2020).
- PvM, also known as calendar or cycle based maintenance, is typically employed to prevent the failure of equipment, minimise the probability of loss of function or maintain an adequate level of dependability, and it requires performing regular maintenance tasks based on a schedule. The underlying assumption is that all equipment or machinery will undergo some degradation over time as it operates (Jimenez et al., 2020). Preventive maintenance is time driven, meaning that maintenance tasks are scheduled based on time of operation, which is based on the number of hours of life cycle a particular equipment or system will work (Motaghare et al., 2018). This maintenance strategy can be divided into two categories: Predetermined maintenance and Condition Based Maintenance (CBM).
- Predetermined maintenance: it lies on actions of maintenance that are based on time intervals established according to historical observations on similar equipment, and to

previously assigned lifetime components. It does not account on actual performance of machinery and it has been often criticised for being a wasteful maintenance philosophy, as for most companies relies on an “over-maintaining” at too large costs (Jimenez et al., 2020).

- CBM: CBM is a type of preventive maintenance that includes a combination of condition monitoring, inspection, testing and analysis. Maintenance actions are driven by the condition of the equipment that is being constantly monitored and analysed, allowing the decision making. CBM can be originated from physical inspections reporting changes in the physically notable attributes of equipment and machinery, being these vibrations or sounds, which can be collected through sophisticated methods such as sensors or other devices to continuously monitor the equipment’s condition (Jimenez et al., 2020). Despite the increase in popularity of smart sensors and instruments, there is a relevant cost associated with these, and are often implemented into critical assets of the business. That is also to say that as this technology gains popularity it will get more and more accessible (Jimenez et al., 2020). The motivation of implementing this strategy is to perform maintenance labours at the exact moment when measured parameters reach unacceptable levels. Once a parameter reaches an unacceptable level, maintenance workers are dispatched (*Compare Predictive vs Condition-Based Maintenance, 2024*). One of the main benefits of this is that rather than just reacting to possible failures, this method foments the possibility to address the root cause of breakdown (Jimenez et al., 2020).
- PdM: PdM can be understood as CBM carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of degradation of the equipment. One of the main principles is to use historical data to detect trends of equipments’ behaviour in order to predict when it will fail. Once failure trends are identified, and the timing of the predicted failure is known, maintenance tasks might be planned-ahead. Typical signs of potential failure may include: increases above normal temperatures, rise in vibration levels or change in vibration spectral pattern, drop in performance levels, increased noise level, change in current and voltages, and many other several things (Jimenez et al., 2020).

Fig 2 below presents a diagram of the different strategies and the main concepts.

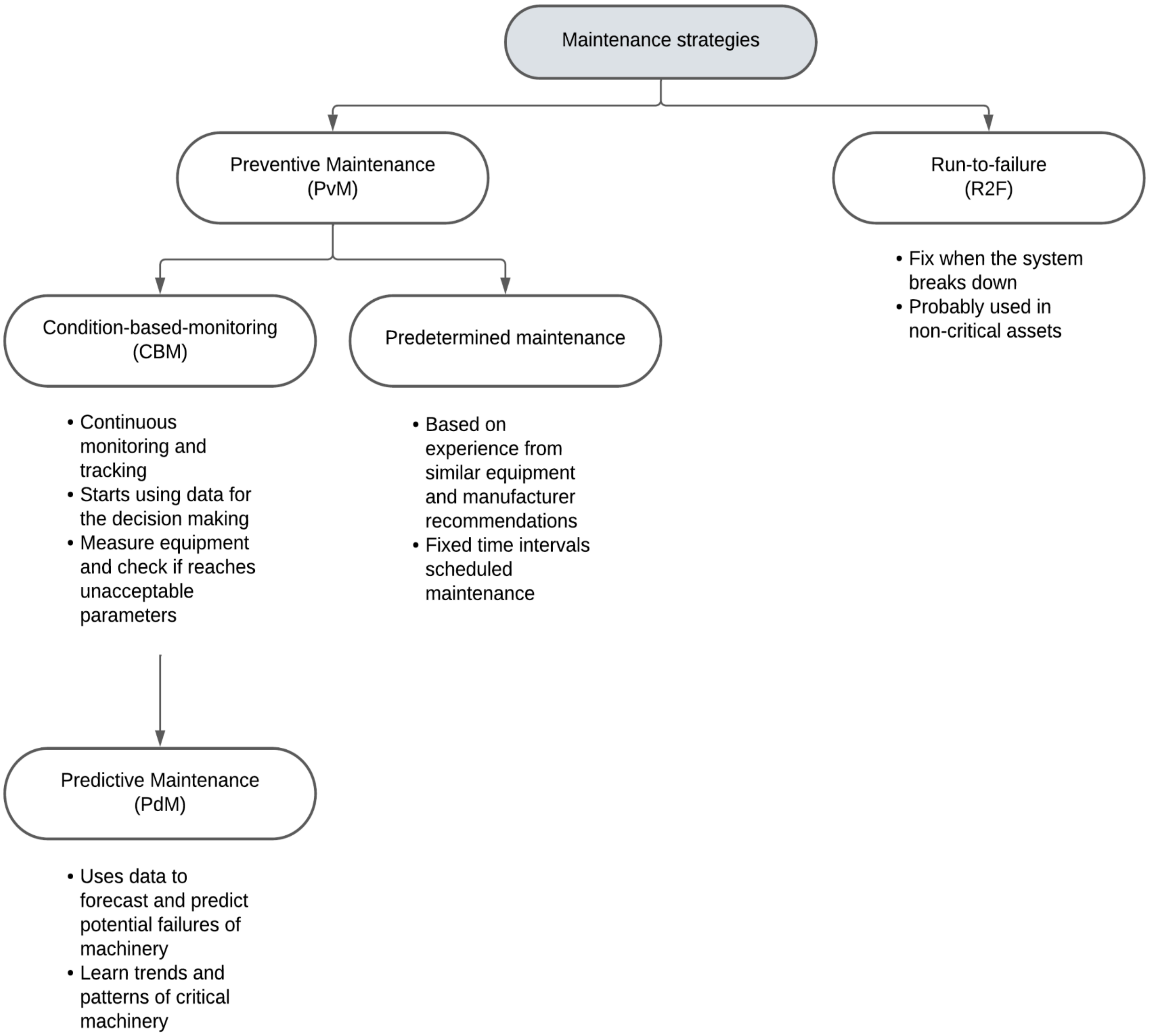

Fig 3 - Diagram of Maintenance Strategies

The next subsection will dig into the maintenance strategies within the maritime sector and its trend and evolution.

4.2 State of maintenance strategies in the maritime sector

One of the challenges of ship maintenance practitioners is the problem of maintenance selection for each equipment, and the decision making process involves utilising different conflicting decision criteria in order to select the optimum maintenance strategy (Emovon et al., 2018). The selection criteria might include features such as 1) Cost: spare parts inventories, materials, labour for each task, crew training… 2) Safety: personnel safety (an equipment failure can yield to serious workers injuries), equipment safety (a system breakdown can lead the entire system to fail) and environmental safety (a system failure can cause environmental hazards), 3) Added value: minimisation of operational loss and equipment reliability and, 4) Applicability: the possibility and accessibility of implementing each of the maintenance strategies to each component (Emovon et al., 2018).

Looking at the evolution over the past years in the field of research, various maintenance strategies have been investigated to ship machinery systems. According to (Karatuğ et al., 2023b), who made a meta analysis based on the articles published between 1999 and 2022 in the field of maintenance strategies for ship machinery systems, these different strategies have evolved from the corrective, preventive, and predictive approaches through the improvement of technology and accumulation of knowledge. Preventive maintenance is currently the most widely adopted strategy in merchant ships, however, with the improvement of CBM and PdM, it has been understood that many unnecessary maintenance operations are performed under scheduled maintenance practices, causing a loss of system usability, an extra workload for marine operators and in the end, a waste of cost (Karatuğ & Arslanoğlu, 2022). CBM has caused an intense interest based on the acquisition of performance data with innovative applications such as wireless sensors, internet of things technology (IoT) specific to the equipment and health status. In this vein, due to its rapid evolution and performance, machine learning and deep learning methods have been used in literature to analyse the collected data from condition-based schemes. Performance predictions, maintenance intervals, failure diagnosis, anomaly detection, system degradation and prediction of remaining useful life are some of the examples. Nonetheless, the lack of open source and analyzable data has been a common problem faced when developing these strategies, and there is already a known issue with the lack of recorded data in the maritime sector. It has been observed that predictive maintenance strategies are considered as an effective maintenance approach for the innovative ship concepts such as all-electric and autonomous concepts (Karatuğ & Arslanoğlu, 2022), but the development of this kind of ships is still in a very early phase. In the analysis made by (Akpinar & Ozer-Caylan, 2022), they mention that new technological developments and requirements of smart advancements could change the environment of maritime business, by the use of big data.

Although not the main field of this research but relevant to mention, external players such as international organisations and legal forces are pushing the maritime industry to achieve environmental targets. The IMO is now entirely dedicated to facilitating the maritime industry to realise carbon neutrality. Regulatory measures have been proposed considering the importance and urgency of green development. The technical approach -through the exploitation of new technologies- plays a key role in the way to realise zero-emission in the industry. In the research made by (Wang et al., 2023), where they focus not only in the green development of the maritime industry but also in the future perspective, they remark on big data analysis as a crucial research opportunity. They suggest that big data analysis should be the key driver to improve environmental performance, by developing predictive systems to estimate emitting resources as energy/fuel consumption, and link them to environmental plans and objectives.

4.3 Benefits of PdM in vessel machinery

If comparing the underlying philosophies of both PvM and PdM strategies, the main differences can be found in Table 1 (Delgado Yanes, 2020):

	Preventive Maintenance (PvM)	**Predictive Maintenance (PdM)**
Reduced downtime	Relies on scheduled maintenance tasks performed at predetermined intervals, which may not always address emerging issues before they lead to downtime.	Identifies potential failures in advance through data analysis, allowing for proactive maintenance scheduling and minimising unplanned downtime.
Cost Savings	Involves regular, scheduled maintenance regardless of equipment condition, potentially leading to higher costs due to unnecessary maintenance activities and parts replacement.	Helps avoid unnecessary maintenance tasks and parts replacements by focusing resources on equipment with imminent failure risks, leading to cost savings in maintenance expenditure.
Data-Driven Decision Making	Decisions are based on predefined maintenance schedules rather than real-time data analysis, limiting the ability to adapt maintenance strategies according to equipment condition and operational requirements.	Relies on data analytics to analyse equipment condition and predict failures, enabling informed decision-making based on real-time insights.

Improved Operational Efficiency	Requires adherence to fixed maintenance schedules, which may lead to inefficient allocation of resources and potential disruption to operations when maintenance tasks are performed regardless of actual equipment condition.	Optimises maintenance schedules based on actual equipment condition, ensuring that maintenance activities are performed only when necessary, leading to improved operational efficiency.

Table 1 - PvM vs PdM

4.4 Seakeeping

Fig 4 represents the diverse variables influencing vessel performance, including factors such as engine degradation, propeller fouling, hull fouling or weather conditions. It provides a good broad overview on how different factors add resistance to the vessel's motion and also represents the importance of considering propeller and hull fouling effects, which as mentioned in the introduction, both aspects are solved and studied by the company. In this project, particular emphasis will be placed on meteorological variables, specially on wind and waves load.

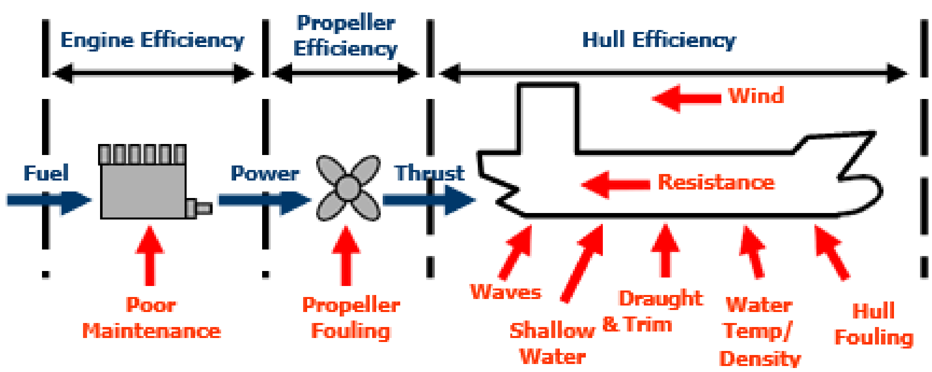

Fig 4 - Variables affecting the ship performance. Extracted from (Chaal, 2018)

Sailing under wind/wave conditions is often identified as seakeeping, where various interactions among ship speed, power, motion and weather conditions are encountered. Ship resistance increases due to wave and wind encounter, and wind effect can contribute to a 2-10% of total ship resistance (Perera & Mo, 2018). The underlying assumption of added wave resistance and added wind resistance is that they increase fuel consumption and power output from the vessel's propulsion system to maintain a consistent speed. To overcome this resistance and maintain the desired speed the engine has to work harder, consuming more fuel and requiring a higher shaft output. The problem is, however, that the ship performance is shown by the speed-power curve from sea trails. But most of the time, this curve is not enough to study the fuel consumption of the whole range of operating conditions such as weather (Ren et al., 2022).

In a situation where the vessel sails with tail winds and tail waves (Fig 5), where the direction of both waves and wind is between 150-180 degrees, the ship experiments and aiding force to its motion. As a result, the vessel would use less fuel and less shaft power for a given speed. Contrary, with sided waves and winds, coming from 30-150 degrees, the stability of the ship is probably affected causing the need to manoeuvre and use additional fuel. Lastly, if the vessel sails against these influential factors, where they come from the front (0-30 degrees), the resistance encountered is high and the fuel consumption and the shaft power should increase significantly to maintain a given speed. Relative wind and waves refer to the direction from which the wind and waves are coming in relation to the movement of the vessel, affecting its performance and stability accordingly (*Apparent wind, 2024*). It can be calculated having the appropriate dataset containing the heading of the vessel, wind direction and wave direction.

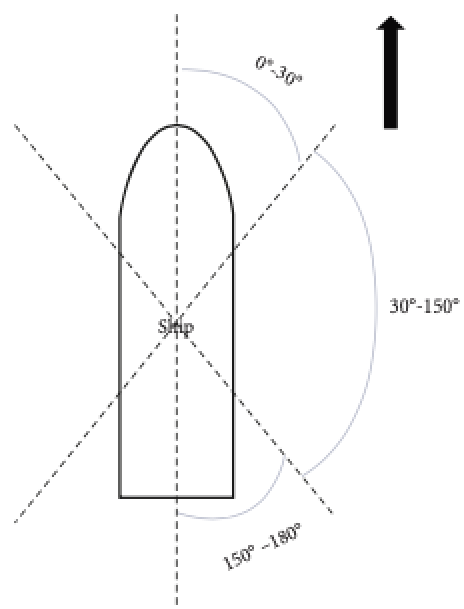

Fig 5 - Wind/wave direction relative to ship's movement. Extracted from (Ren et al., 2022)

Traditional approaches to address vessel performance under seakeeping conditions typically cover physics-based solutions. These solutions aim to understand the mechanics of how weather elements influence vessel behaviour. However, with the progress and growth of technology and data-driven methodologies, modern approaches have emerged and leverage vast amounts of data to model and predict these effects.

4.5 Physics-based approaches

These methods depend on mathematical models and fluid dynamics principles to replicate the interaction between a vessel and its environment (Guo et al., 2023). Towing tank experiments and numerical simulations with computational fluid dynamics (CFD) are prime examples of physics methods for examining wave and wind resistance. Towing tank experiments use scaled-down models of vessels that are towed through a controlled water environment to assess their resistance and performance (see Fig. 6) (Larsson, 2010). CFD simulations rely on computational models to offer information about hydrodynamic forces (Ferziger et al., 2019). In general, ship model tests estimate the required ship power/thrust levels for a selected range of ship speeds for a down-scaled version of the ship. These same experiments can be done and extrapolated into rough weather situations (simulate waves), where the respective vessel faces speed reductions due to the variations in ship resistance, and power/thrust propulsion efficiency can be calculated. The same results can be verified under real sea trail results, which consist of measuring the required ship speed and power values under various wind and wave conditions (Perera & Mo, 2018).

Fig 6 - Example of model test on a towing tank. Extracted from (Landowski, 2015)

Despite wave loads can be estimated from sea-keeping tests, such tests are both expensive and really time consuming. As an alternative to these tests, there are other approaches to obtain wave transfer functions, as is the case of numerical simulations. However, validating it for a current ship would present an additional challenge (Guo et al., 2023).

4.6 Data-driven approach

As mentioned in section *4.2 State of maintenance strategies in the maritime sector* the direction of the marine industry is moving towards data-driven approaches where sensors collect in-service data. This makes it possible to learn the relationship between variables representing external vessel factors and engine operations (Guo et al., 2023), and the benefits of it are:

1. Real world experience: If a data based approach is implemented, it would provide a broader context of vessel performance in an unlimited sailing scenarios. It would capture and learn from the vessel's experiences itself.

2. Cost-effectiveness: Experiments and simulations can be expensive and time-consuming, requiring physical models, specialised equipment and highly skilled professionals with a lot of domain expertise in different areas. In contrast, a data-driven approach can work with the available information from historical weather record databases and vessel monitoring systems, potentially saving money as well as time spent on testing.

3. Scalable: data-driven solutions are also scalable to analyse large amounts of vessels data, which set a good framework that can be easily scaled by fleet-owners among different vessels.

4. Flexibility: data-driven models can be routinely renewed and adjusted as soon as new datasets are collected, allowing the ongoing enhancement of adaptation to changing conditions or technologies.

5. Accessible: Data-driven approaches are also likely more accessible to researchers and industry practitioners that do not have access to simulations, or the ability to perform experiments.

4.7 Related works, data leverage combining meteorological effects and ML

In this section some of the advantages that are just mentioned previously will be exemplified, where different researchers promote innovative solutions using in-service data of different case studies. Voyage planning, route optimisation or performance KPIs are some of the main topics developed.

(Liang et al., 2019) predicted ship propulsion power under varying weather conditions. In their work, they compared the efficacy of physics-based Vs. machine learning approaches. They showcased the utilisation of AIS data, ship propulsion power measurements, and weather data in order to develop improved predictive models. By comparing traditional machine learning methods with deep learning architectures, the authors achieved good results in prediction accuracy. Machine learning models outperformed physics-based approaches, as evidenced by higher R2 scores. One of the reasons for ML to outperform traditional methods might be the difficulty to capture and analyse complex features in large datasets. (Ren et al., 2022) contributed to the field addressing the limitations of existing fuel consumption models, which often overlook the influence of weather conditions. Their research introduced a regression algorithm designed to estimate fuel consumption under varying weather conditions during voyages. Leveraging inputs such as MRV daily fuel consumption, wind speed, wave height, ship speed, draught, AIS segment distance, and ship's heading, the study evaluated three types of models, based on similar logic. Through rigorous testing across four container ships over a year-long period, one of the proposed models got promising results, achieving an average error of less than 3% when compared to real fuel consumption data. (Guo et al., 2023) addressed the ship's technical performance -or engine state over time- evaluation using physical and ML-based approaches. The study introduced the Vessel Technical Index (VTI) proposed by DNV, as a promising KPI which was expected to represent the change in technical performance of ships over time. VTI was based on isolating the technical performance of a ship by accounting and correcting for relevant operational and weather effects, and in practice, it represented the increase in power demand for the ship in calm water condition, compared to new-built state. Therefore, this KPI could be used to monitor a ship’s technical performance over time and ship owners could rely on it for planning maintenance schedules for their fleets. (Gkerekos & Lazakis, 2020) also employed a data-based approach utilising deep learning to estimate FOC under varying conditions, integrated within a route optimization process. Their final solution would find the most optimal route according to weather conditions. Their study incorporated data parameters such as draft, engine speed, engine FOC, engine power, vessel speed, currents, swell significant height, and wave direction. Different KPIs for maintenance practices were presented in their study too.

Overall, these works incorporated the impact of the weather on: 1) Engine shaft propulsion power prediction, 2) Fuel consumption estimation over different conditions combined with voyage planning and, 3) Correcting and isolating weather load for ship engine performance analysis over time -KPIs.

Table 2 consists of a summary of which models and data have been used across the different studies mentioned above. In some of the cases both traditional machine learning and deep learning (DL) models have been tested. Choosing between developing a traditional ML or DL model depends on various factors. For example, traditional ML algorithms, such as linear regression and decision trees, can be computationally efficient and faster, and perform well when the dataset contains linear relationships. On the other hand, DL works well handling non-linear and high-dimensional datasets. Hence, DL models, such as artificial neural networks (ANNs), often require longer training time, higher computational resources and hyperparameter tuning. The choice between traditional ML and DL depends on the specific task, the nature of the data, available resources, and the desired level of interpretability versus predictive performance (Wolfewicz, 2023).

Authors & Year	**Details**	**Data**	**Models**	**Relevant Findings**
Liang et al. (2019)	Predict engine shaft propulsion power and behaviour under different weather conditions	AIS data, ship operational data and weather data	Machine Learning: Gradient Boosting Decision Tree, AdaBoost Decision Tree, Random Forest, SVM Deep Learning: ANN	Machine learning outperformed in two scenarios traditional physics-based models, R2 score increased, i.e., from 0.48 to 0.78. Both traditional ML and DL made good predictions, and data-driven models strongly rely on the data they have been trained by
Gkerekos & Lazakis (2020)	Fuel estimation based on weather conditions for route optimisation. Combined with Dijkstra's algorithm to select optimal routes. Introduction of KPIs for ship efficiency and performance for maintenance practices	Ship operational data and weather data	Deep Learning: ANN	An R2 of 89.4% was obtained while predicting the vessel’s fuel consumption in a case study, and five optimal routes were identified and ranked for two sailing speeds corresponding to

				different operating profiles (ballast and fully loaded)
Ren et al. (2022)	Fuel estimation under varying weather conditions. MRV report is used as reference of fuel consumption.	AIS data, ship operational data and weather data	Machine Learning: Ridge Regression	The result shows that most of the models did well fuel consumption predictions, and the best was a MRV-based ML model that could predict under different weather scenarios with an average error less than 3% compared to real MRV report
Guo et al. (2023)	VTI as a representation of technical ship performance over-time. Correct the shaft power from weather and operational loads	Ship performanc e data and weather data	Machine Learning: PLS Deep Learning: ANN	The mean trend of VTI over time, representing the change in performance of the ship (PdM), is quite comparable. Physics-based approach helped in removing uncertainty, whereas the data-driven approach creates an opportunity for ship performance monitoring without the need for speed-through-water measurements, which are considered unreliable for most ships

Table 2 - Summary of models developed, findings, data used and goals among relevant studies

5. Data analysis

5.1 Approach overview

The in-service data used for the development of this project belongs to a chemical tanker vessel powered by a diesel BERGEN B32:40L 8P engine, with a maximum RPM of 750, which has been sailing between north Europe and mid Africa over 6 months. During its journeys the ship has been monitored and has made available detailed minute-by-minute data. The data covers various aspects of the ship's engine performance, and includes variables such as how much fuel the ship consumes, how the shaft power is utilised, and other important factors. This data was collected from June 2023 to February 2024. In order to complement this operational information, meteorological data retrieved from the stormglass.io API has been tracked for the same vessel based on its GPS location. It does this at hourly intervals, providing insights into meteorological conditions such as wind speed, wave height, swell direction, and ice coverage.

An overview of the process can be seen in Fig 7, where:

1. The process starts with data acquisition and preprocessing, where NaN values are managed, duplicates are removed and outliers are identified and addressed. Filtering techniques are also applied in each dataset to ensure data quality and integrity.

2. The two primary datasets are combined. This involves synchronising the time frequencies between the datasets to facilitate the analysis. Also, new features are created to capture the influence of weather on vessel performance, including indicators for tailwind or headwind, tail waves or head waves. This will help in visualising the data and building the logic behind the end solution.

3. After some exploratory analysis, a near-calm-water dataset is defined to serve as a reference for comparing the additional loads experienced under different scenarios. This part is developed by fitting a polynomial curve. The values on the curve represent each “ideal” shaft power and/or fuel consumption that the vessel would need to sail at a given speed with calm waters.

4. Then, in the model development phase, a XGBRegressor model is employed, trained and tested to predict the impact of weather fuel consumption. This is done using new features created in the section before, where knowing for each speed what would be the reference shaft power or the reference fuel consumption (under calm waters), new columns can be calculated. These columns' names are extra_shaft_power and fuel_overconsumption, and will be interpolated based on the polynomial curve.

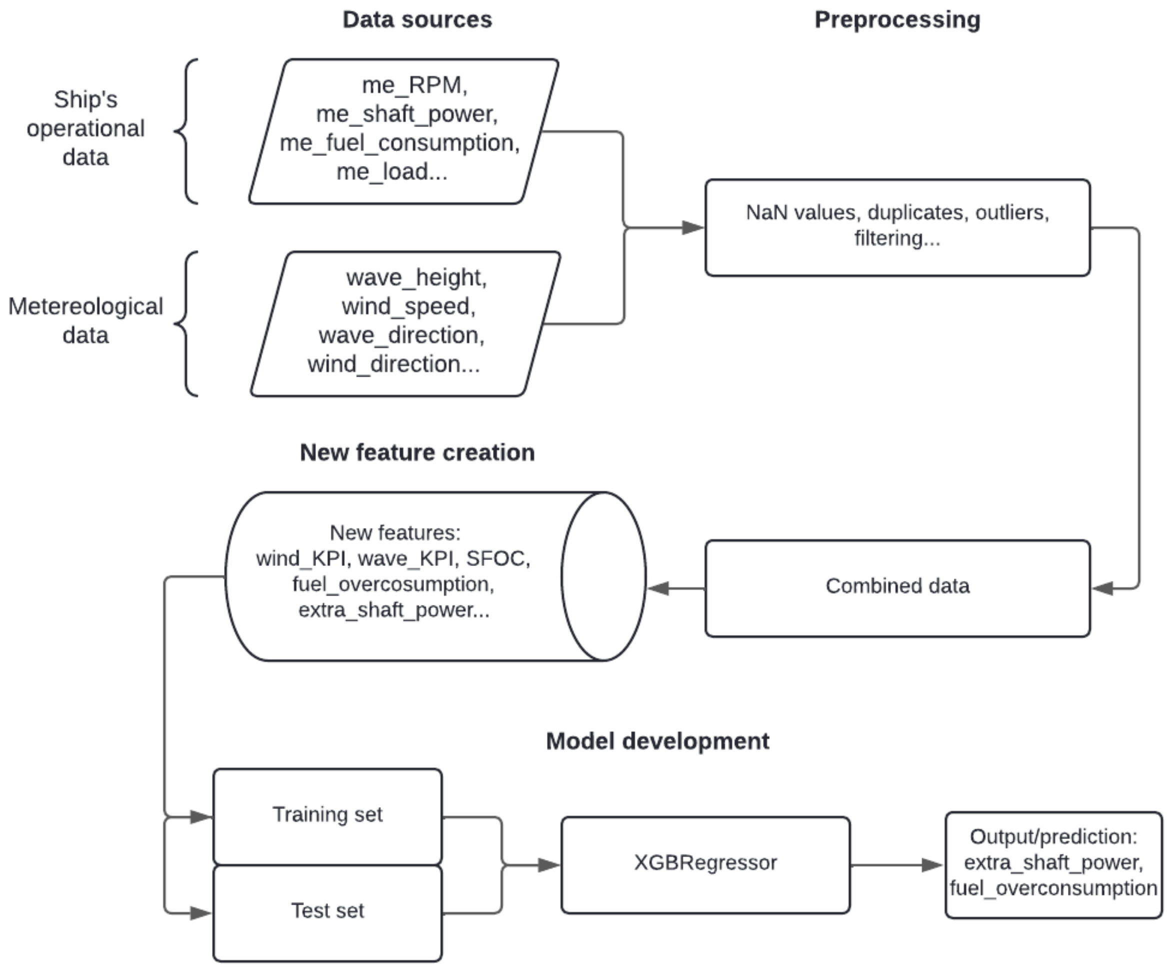

Fig 7 - Approach overview.

5.2 Data acquisition

5.2.1 Ship operational data description

The ship operational data utilised in this project is stored in SQL format within a MariaDB database, facilitating efficient storage and retrieval. The tabular data employed for analysis encompasses a range of essential columns, each providing valuable insights into the vessel's performance and operations:

Column Name	Description	Unit
timestamp	Timestamp indicating the time of the recorded data, every minute	YYYY-MM-DD HH:MM:SS
me_1_load	Measurement of engine 1 load	percentage (%)
log_speed	Log speed of the vessel, over the water and not over the ground	knots
frugal_status	Status indicating whether the vessel is operating in frugal mode	Values: 0 to x
me_1_rpm	Engine 1 revolutions per minute (RPM)	rpm
me_1_fc_mass	Mass flow rate of fuel consumption for engine 1	kg/h
shaft_1_power	Power measured at shaft 1	kW
heading	Heading or direction of the vessel	degrees (°)
draft_fwd	Forward draft from sensor or manual input	m
aux_1_fc_mass	Aux engine forward mass flow	kg/h
aux_2_fc_mass	Aux engine return mass flow	kg/h

Table 3 - Ship Operational Data description

5.2.2 Meteorological data description

The weather data utilised in this project is obtained through the marine weather API provided by stormglass.io. This API enables the retrieval of real-time weather information customised to the precise GPS coordinates of the aforementioned vessel. The collected data is also stored in SQL tabular format within a MariaDB database:

Column Name	Description	Unit
sg_timestamp	Timestamp indicating the time of the recorded weather data	YYYY-MM-DD HH:MM:SS
wind_direction	Direction from which the wind is blowing	Degrees (°)
wind_speed	Speed of the wind at the vessel's location	m/s
wave_direction	Direction from which waves are approaching	Degrees (°)

wave_height	Vertical dimension of waves nearby	m
wave_period	Time duration between successive waves	s
air_temperature	Temperature of the air at the vessel's location	Celsius (°C)
humidity	Relative humidity level in the air	Percentage (%)
latitude	Latitude coordinate of the vessel's location	Decimal degrees
longitude	Longitude coordinate of the vessel's location	Decimal degrees
water_temperature	Temperature of the water at the vessel's location	Celsius (°C)

Table 4 - Meteorological Data description

Table 5 and 6 contain one data sample from each dataframes, ship operational and meteorological data:

timestamp	**me_1_load**	**log_speed**	**frugal_status**	**me_1_rpm**	**me_1_fc_mass**	**shaft_1_power**
2024-01-31 16:22:15	38.2250	5.08333	0	729.308	173.507	398.830
heading	**draft_fwd**	**aux_1_fc_mass**	**aux_2_fc_mass**	**Ship Operational Data sample**		
31.2	6.6	271.259	236.643			

Table 5 - Ship operational data sample

sg_timestamp	wind_direction	wind_speed	wave_direction	wave_height	wave_period	air_temperature
2023-06-01 00:00:00	170.22	6.62	186.89	2.42	7.91	24.35
humidity	**latitude**	**longitude**	**water_temperature**	**Meteorological Data sample**		
81.00	-7.64128	7.381360	26.78			

Table 6 - Meteorological data sample

The amount of rows before any preprocessing are 352.580 for ship data and 5.880 for weather data (consider that this last one is in hourly frequency).

5.3 Data pre-processing and filtering

The in-service data measured and recorded onboard a ship is known to have issues as well as measurement noise (Guo et al., 2023). This step is performed individually on each dataset. Processing data individually allows for tailored and focused cleaning and validation procedures. The main steps followed have been: 1) Data filtering if needed, 2) Spot clearly wrong values -or anomalies, 3) Check for duplicates , 4) Check for NaN values.

5.3.1 Ship operational data cleaning

The data that belongs to vessel operations has been filtered out to ensure only vessel sailing conditions, focusing on data points where the log_speed is greater than 4,5 knots and the shaft power is greater than 250 kW. By these filtering, scenarios such as manoeuvring or deceleration have been taken out, ensuring vessel operational and sailing data (Guo et al., 2023). Then, wrong values have been spotted and filtered out. For example, a minimum value of -277.15800 for "me_1_fc_mass" can be seen when running the Python .describe( ) method, which is obviously wrong. These anomalies and outliers are removed from the dataset. No duplicate nor NaN values are found.

The end result after the cleaning and validation process leaves the ship operational data with 201.101 rows, which makes sense since around 60% of the data collected for each vessel refers to sailing conditions (this information is provided by the company). Relevant to mention is that deeper cleaning or data filtering might be done later in the process, depending on the requirements of each step.

5.3.2 Meteorological data cleaning

Weather data contains 67 rows with missing values, located in wave_direction, wave_height and wave_period. These 67 NaN values represent a 1,13% of the whole dataset, and assuming that wave conditions don't change drastically from one hour to the other, the way of handling these values is by interpolation. Data interpolation is a crucial step in data preprocessing, and it estimates unknown values within the range of known data points. It takes existing data points to infer and fill in missing or unknown values (*What is data interpolation?* 2024). Duplicate nor outlier values were found in this dataset. Additionally, in order to have minute frequency data, sg_timestamp was set as an index, and then using the Python .resample('T').ffill() methods, each hourly data value was resampled to a 60 minute frequency. The underlying assumption behind this is that sea estate might remain steady in the range of 1 hour. Hence, this would allow for a later data combination, adding external weather factors to the ship's operational data, gaining context and more explainability on the engine's behaviour. The result for the meteorological data after applying these preprocessing techniques was 352.741 rows.

The two preprocessed dataset were saved in a parquet file and then combined using the pd.merge() method. It is done to take each dataset's index as a reference and combine the data where the index (in this case, the timestamp) coincides. Although not crucial, a few steps such as rounding the timestamp to the closest minute before or modifications on the dtype for some columns were necessary to succeed with the merging phase.

5.4 New feature creation

In this section, new features called wind_relative_dir and wave_relative_dir are introduced to help in understanding the impact of wind and waves on the vessel's performance. These features serve to define whether the wind and waves are hitting the vessel from the back, front, or side, and to explain their effect on shaft power or fuel consumption. By utilising the vessel's heading alongside wind and wave direction data, these metrics are calculated.

5.4.1 Wind relative direction

The function takes two input parameters: wind_direction, representing the direction from which the wind is blowing, and vessel_heading, referring to the heading or direction of the vessel.

The function begins by computing the relative wind direction (where the wind is coming from compared to the direction the vessel is facing) by subtracting the vessel's heading from the wind direction. This step determines the angle between the wind direction and the vessel's heading. Subsequently, the relative wind direction is normalised to ensure it falls within the range of -180 degrees to 180 degrees, providing a standardised measure for comparison.

The wind category is then determined based on the normalised wind direction. If the normalised wind direction falls within the range of -45 to 45 degrees, it indicates that the wind is against the vessel's motion. Similarly, if the normalised wind direction falls within the range of 135 to 180 degrees or -180 to -135 degrees, it suggests that the wind is pushing the vessel from the tail. For all other cases, where the wind direction falls outside these ranges, it indicates that the wind is hitting the vessel from the side.

Finally, the function returns a numerical value representing the wind category: 0 for against, 1 for pushing, and 2 for side. Fig 5 from section *4.4 Seakeeping* might help understanding this classification.

The values for each row are stored in a new column called wind_relative_dir, generated calling the function applied to the wind_direction and heading columns of the dataset using the apply method combined with a lambda function.

5.4.2 Wave relative direction

With a very similar approach, the wave direction in relation to the vessel is also calculated. This function takes two input parameters: vessel_direction, representing the heading or direction of the vessel, and wave_direction, denoting the direction from which waves are coming.

The function begins by ensuring that both the vessel and wave directions are normalised to fall within the range of 0 to 359 degrees, simplifying subsequent calculations. Next, it calculates the relative direction of the waves with respect to the vessel by subtracting the vessel direction from the wave direction and then making sure that the result falls within the range of 0 to 359 degrees.

Based on the relative direction of the waves, the function categorises the influence of wave direction into three categories: If the relative direction falls within the range of 120 to 240 degrees, it indicates that the waves are coming from the back of the vessel, returning a value of 2. If the relative direction falls within the range of 0 to 60 degrees or 300 to 360 degrees, it suggests that the waves are coming from the front of the vessel, returning a value of 0. For all other cases, where the relative direction falls outside these ranges, it means that the waves are hitting the vessel from the side, giving it the value of 1.

The values are stored in a new column called wave_relative_dir, created by calling the function and using the wave_direction and heading columns of the dataset. It is also done by using the apply method and the lambda function.

5.4.3 SFOC (Specific Fuel Oil Consumption)

Despite not being within the extent of this project to recalculate this indicator and find degradation patterns, the Specific Fuel Oil Consumption (SFOC) plays an important role as it is the KPI that serves as the foundation of the idea of PdM within the company. The SFOC is a key performance indicator used in the maritime industry to measure the efficiency of marine engines. It represents the amount of fuel consumed by the engine per unit of power generated, typically expressed in grams per kilowatt-hour (g/kWh) or kilograms per megawatt-hour (kg/MWh). A basic assumption is that as we see a decrease in efficiency, there might be a pattern of degradation. To calculate this value (*Brake-specific fuel consumption, 2024*):

- SFOC: fuel consumption / shaft power.

The main idea behind using this indicator is looking at its evolution over time and addressing any degradation patterns through the use of data. However, there are some things that need to be taken into consideration to understand this indicator. If we look at Fig 8, where the X - axis represents the engine load and the Y - axis represents the KPI, it can be seen that for every engine load the values of the SFOC might vary quite a lot, giving many different efficiency results for the same load. This variation occurs as fuel consumption and shaft power, which are the values used for the calculation of the SFOC, are influenced by internal and external variables. Understanding how the weather affects the fuel consumption and shaft power variations indirectly helps in understanding the variations of this KPI, and therefore, is one step ahead to a PdM solution.

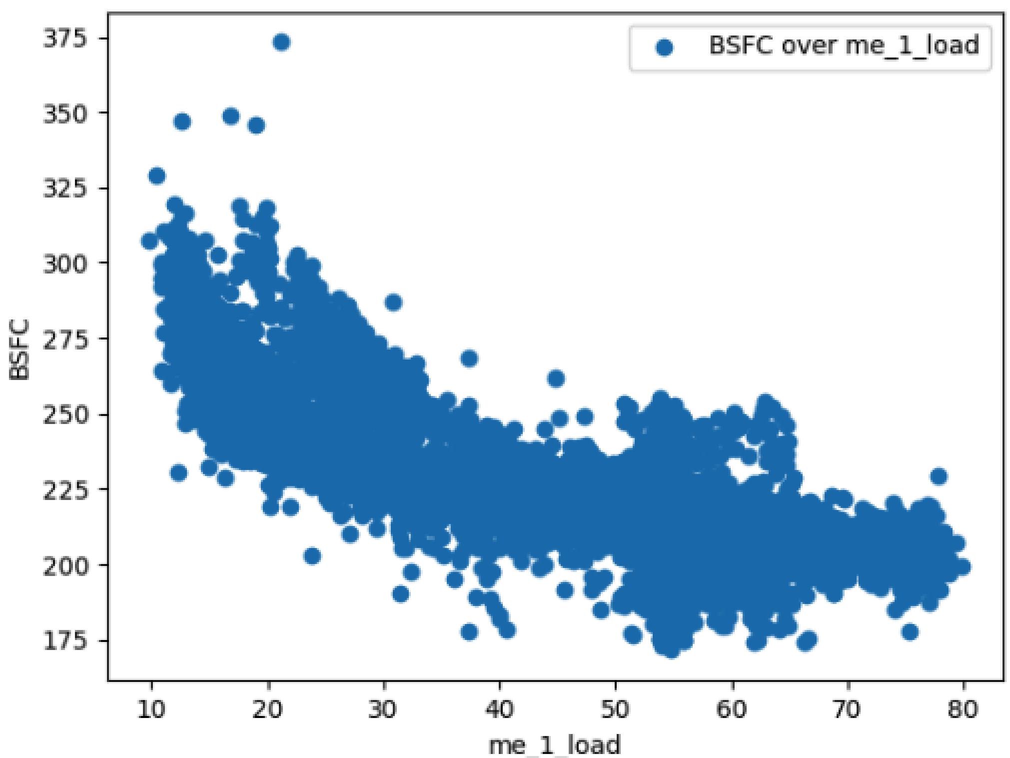

Fig 8 - example of BSFC/SFOC values for engine load

5.5 Data visualization

This section focuses on applying data visualisation techniques to get insights from the in-service collected data. The main goals include understanding significant correlations within the dataset and visualising the impact of weather variables on different features. Using visualisation libraries such as matplotlib and seaborn, the analysis aims to explain patterns, relationships, and trends in the data.

Fig 9 presents a correlation matrix for the feature variables. A correlation matrix is a statistical technique that shows how strongly different variables are related to each other in the form of a table. Each row and column in the matrix represents a different variable, and the numbers -or correlation coefficients- in the cells indicate the strength and direction of the relationship between them (Wagavkar & Sanskar, 2023). A correlation value close to +1 indicates a strong positive relationship, while a value close to -1 indicates a strong negative relationship. A value close to 0 suggests little to no relationship between the variables. In practical terms, a positive correlation would indicate that as the value of a specific variable increases, the other variable would increase as well. Contrary, in the case of a negative correlation, as one variable would increase, the other variable would decrease. A correlation matrix can be a fundamental tool in machine learning. Understanding the strength and direction of these variable relationships, machine learning models can better comprehend the underlying patterns in the data and make more accurate predictions. Variables with strong correlations may be redundant for the model, while variables with weak correlations may provide unique information. Thus, analysing the correlation matrix is important for feature selection and building good machine learning models (Zipporah, 2021).

Firstly, when looking at at Fig 9, the correlation matrix reveals stronger correlations among engine parameters that operate in synchronisation:

- The correlation coefficient of 0.89 between shaft_1_power and me_1_fc_mass indicates a robust positive correlation. This suggests that as the power generated by the shaft increases, so does the fuel consumption, which aligns with the expected behaviour of the vessel's engine system.

Among the variables that represent meteorological occurrences:

- The correlation coefficient of 0.66 between wave_height and wave_period indicates a positive relationship. This suggests that as the height of the waves increases, so does their period or the time duration between successive waves.
- A correlation of 0.56 between wind_speed and wave_height suggests that strong wind speeds are associated with increased wave heights. Strong winds might reveal storm signs, which bring at the same time bigger waves.
- A correlation of 0.49 between wind_direction and wave_direction signifies that the direction from where the wind is blowing and waves are coming change with quite a strong relationship. Wind and waves come from the same direction in many situations.

Lastly, one of the most significant correlations for this analysis, is the relation of a particular variable from the ship operational data with two of the weather variables:

- The negative correlation coefficients (-0.46, -0.43) between wave height, wind speed and log_speed suggest that adverse weather conditions, such as high waves and strong winds, are associated with decreased vessel speed. This indicates that rough weather may impede the vessel's progress, adding resistance during the voyage. Therefore, ship speed power performance emerges as a focal point in this analysis.

Ship speed power performance refers to the relationship between the speed of a vessel and the power required to maintain that speed, as well as the resulting fuel consumption. This performance is particularly important when additional shaft power is needed and fuel consumption increases to maintain certain speeds. Thus, given the observed correlations with wind and waves, the analysis will continue to explore how these variables affect shaft power and fuel consumption.

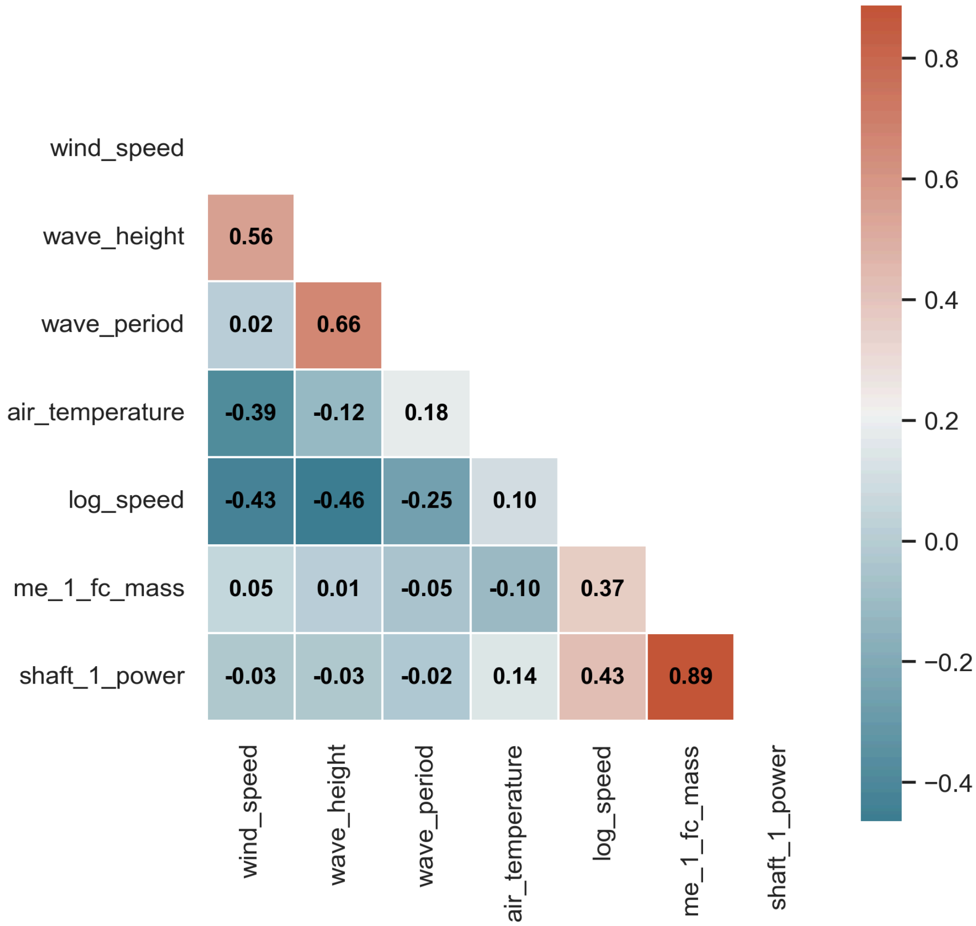

Fig 9 - Engine and weather feature variables correlation matrix

Histograms of the distribution for each feature variable can be seen in Fig 10. Most of the time, wind speeds are between 3 to 7 m/s, but there's still data for other wind speeds too. This variety is good as it provides a wide range of weather conditions to study, and the model can learn from them too. Wave heights are typically between 1 to 2 m. Additionally, it seems that the vessel usually travels at a speed of 11 knots, as indicated by the log speed data. Variables like me_1_load, me_1_rpm, and shaft_1_power have similar distributions. It also appears that the frugal status feature is commonly used in vessel operations, which reflects the aim for a more efficient sailing. These visualisations provide a broad picture of the typical distribution of data points for each feature variable, offering valuable insights into their frequency and range of occurrence.

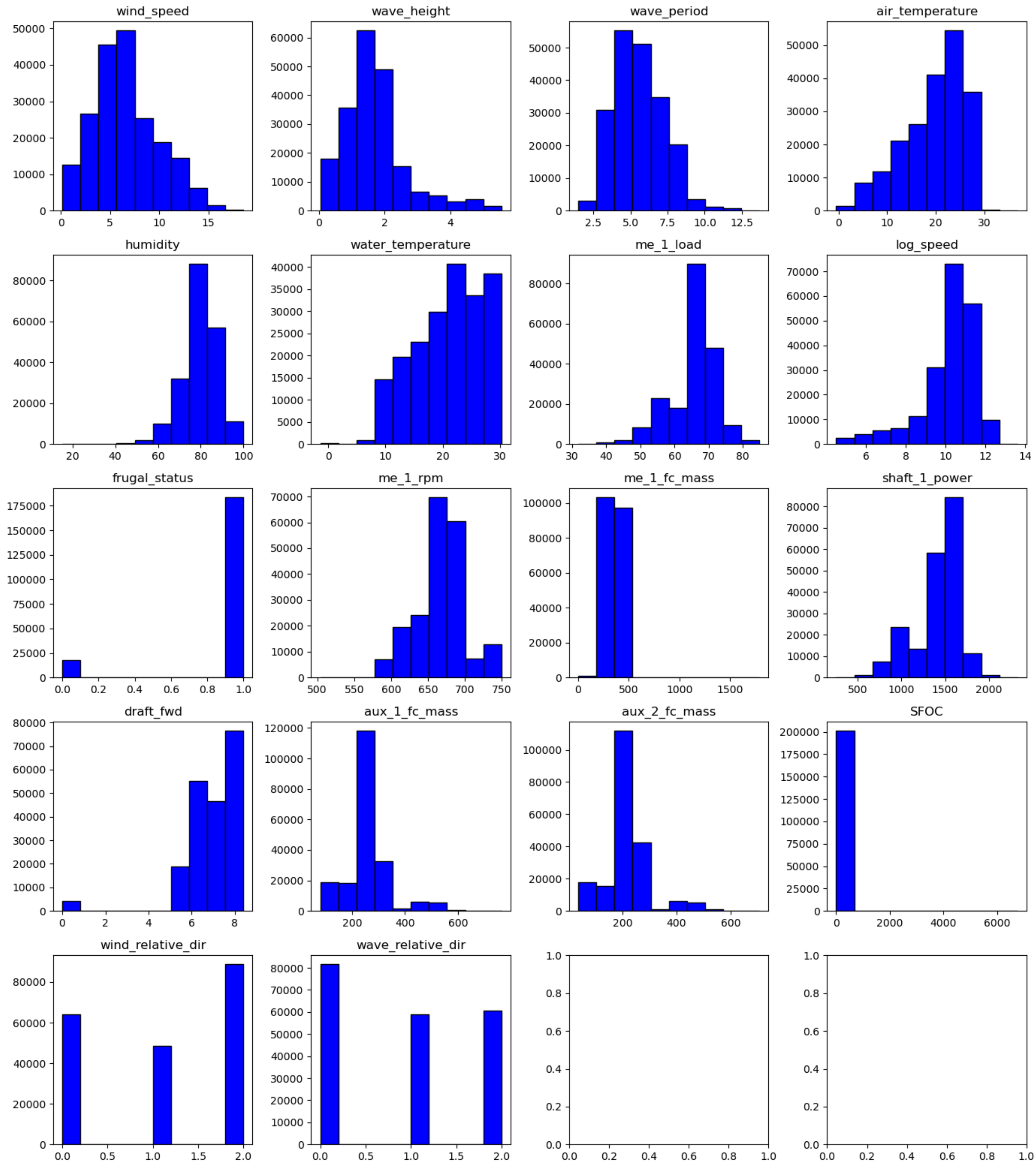

Fig 10 - Feature variables distribution

In Fig 11, two scatterplots are displayed side by side. The first scatter plot illustrates the relationship between shaft power and sailing speed, with the Y axis representing shaft power and the X axis representing speed. Similarly, the second scatter plot reflects the relationship between fuel consumption and sailing speed, with the Y axis representing fuel consumption. Both scatter plots include trend lines. The trend line increases in each case for higher speeds. More shaft power and more fuel are demanded at faster sailing speeds. However, the data points are scattered, suggesting variability in the relationship between shaft power, fuel consumption and log speed. To enhance interpretability and gain deeper insights into this relationship, weather features will be incorporated into the analysis, as shown in Fig 12.

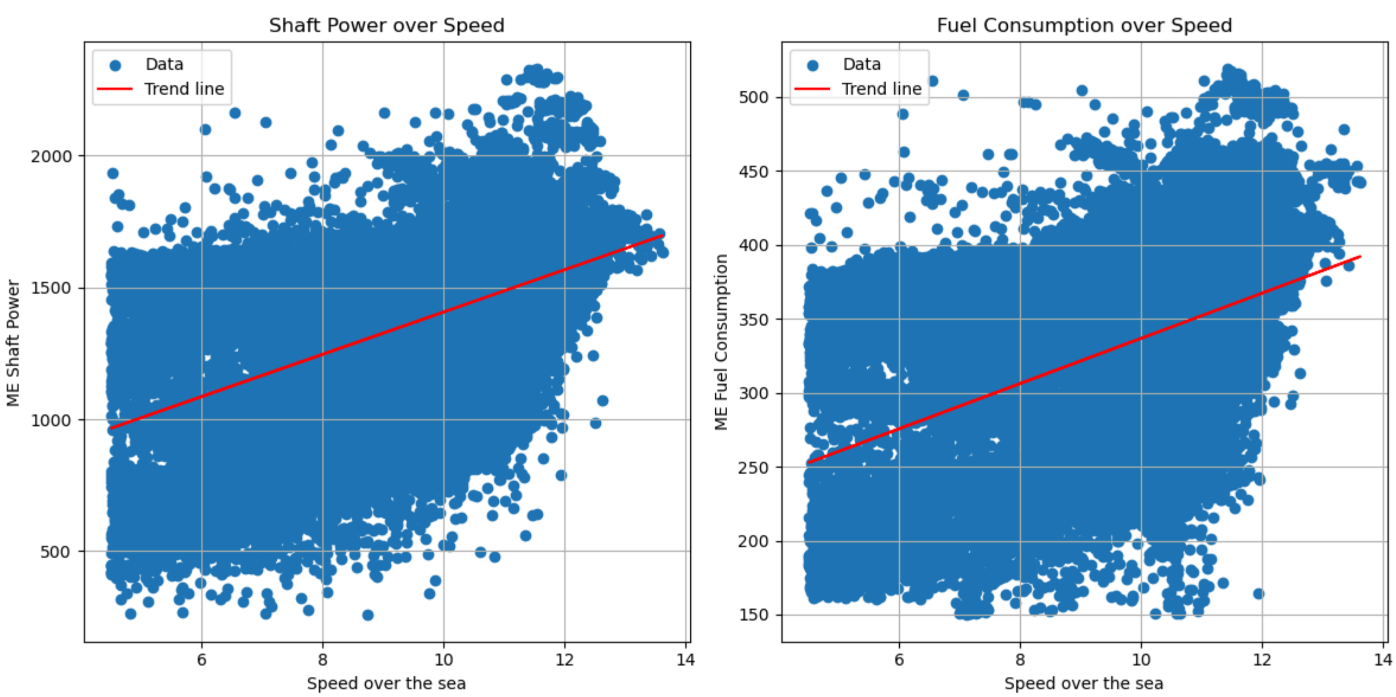

Fig 11 - Scatter Plot of ME Shaft Power and Fuel consumption over different speed with Trend Line

When adding weather variables such as wind speed and wave height through a colorbar in Fig 12, there are distinct areas where colours are more intense, indicating specific weather conditions. In the left chart, intense green-yellow colours correspond to wind speeds ranging from 12.5 to 17.5 m/s, while in the right chart, similar colours represent greater wave heights of 3 to 5 m. These areas or operating zones explain periods of intense weather conditions that carry significant loads on both shaft power and fuel consumption. They also reveal engine behaviour. For instance, with the same shaft power, the vessel may achieve speeds of 6 to 7 knots during intense weather conditions (green-yellow dots), whereas in calm weather (dark blue), speeds of 11 to 12 knots, nearly double, can be reached. This effect is shown in fuel consumption as well, Fig 13.

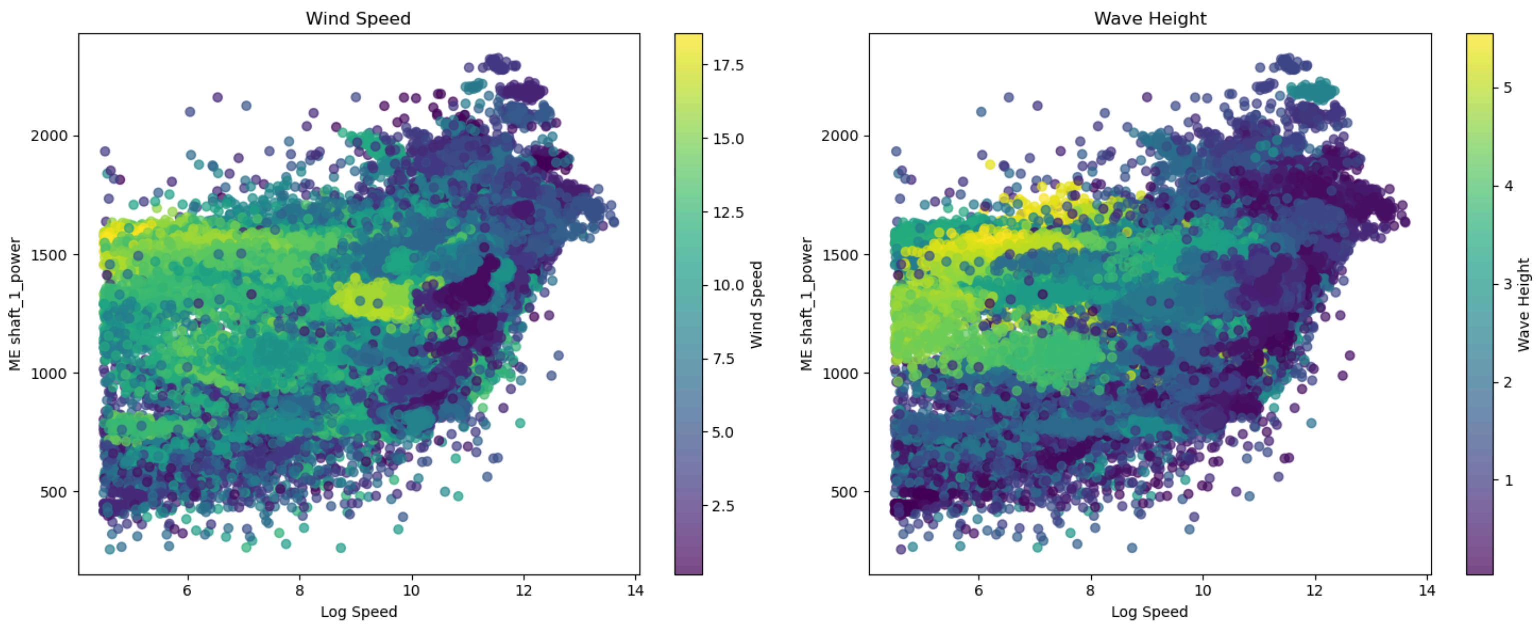

Fig 12 - Scatter Plot of Shaft power over different speed with wind and wave intensity indicator

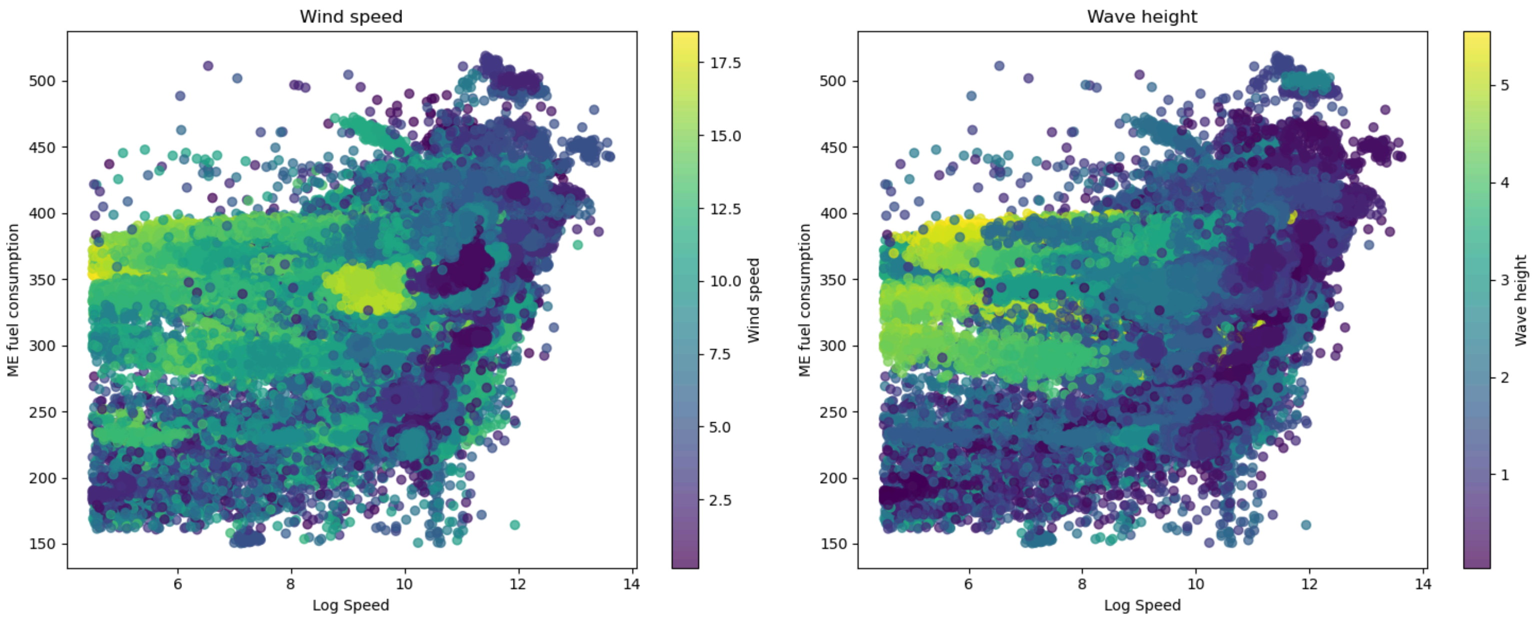

Fig 13 - Scatter Plot of Fuel consumption over different speed with wind and wave intensity indicator

In the scatter plot with wave relative direction (categorization) in the colour bar (Fig 14), dark colours represent waves coming from the head, green represent side waves, and yellow represent tail waves. Focusing on shaft power values around 1500 kW, the red rectangle shows how log speed is impacted by wave direction for the same shaft power. When facing head waves, represented by dark dots, the vessel's speed is notably lower compared to when waves aid its forward movement, resulting in significantly higher speeds for the same shaft power. It's worth noting that 1500 kW is chosen as the reference shaft power due to its high occurrence count (Fig 10), making it a representative value in the dataset. Additionally, the fewer occurrences of yellow dots may suggest less prevalent occurrences of tail waves in the dataset when the shaft power is 1500 kW (see Fig 15).

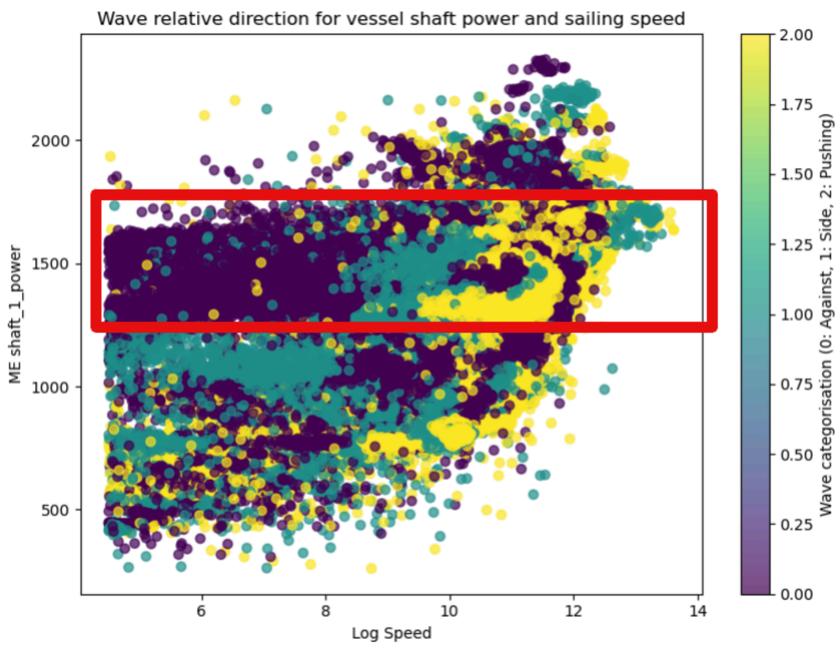

Fig 14 - Scatter Plot of Shaft power over different speed with wave relative categorization

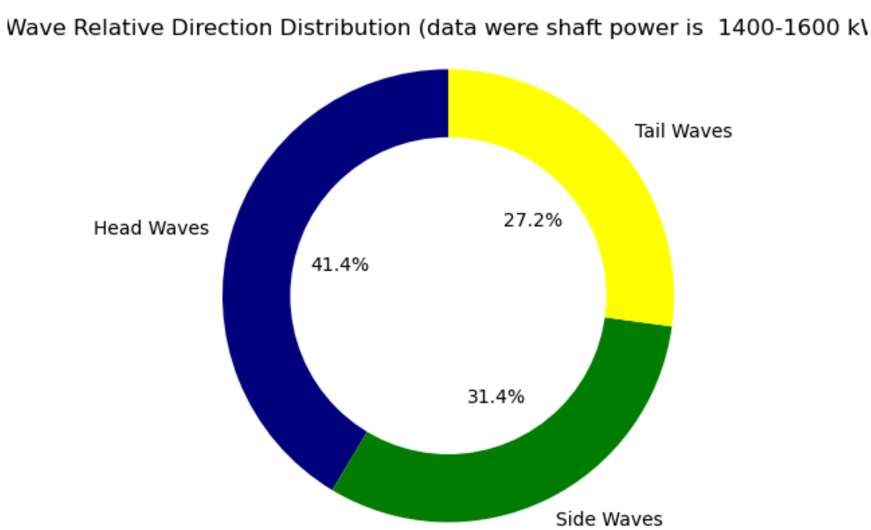

Fig 15 - Wave Relative Direction Distribution (data were shaft power is 1400-1600 kW)

Considering that the speed is one of the most significant outputs generated by the vessel engine, Fig 16 represents an OLS test summary, providing insights into the relationship between various factors influencing the SPLS (Shaft Per Log Speed) ratio. This ratio is calculated by shaft power / log speed and represents how much shaft power is required for every unit of speed.

The Ordinary Least Squares (OLS) test is a statistical method used to explore and quantify relationships between variables. In this analysis, the method is employed to understand how wave characteristics (such as wave height and wave KPI), wind speed, water temperature, and air temperature impact the dependent variable: SPLS ratio.

Breakdown of the test summary:

- **Dependent Variable:** SPLS (Shaft Power to Log Speed Ratio). How much power is needed for each speed unit.
- **R-squared**: The coefficient of determination, which measures the proportion of the variance in the dependent variable that is predictable from the independent variables. In this case, the R-squared value of 0.422 indicates that approximately 42.2% of the variance in SPLS is explained by the independent variables in the model.
- **F-statistic**: A measure of overall significance of the regression model. In this case, the F-statistic is 1.824e+04, indicating that the overall model is statistically significant.
- **Coefficients (coef)**: These represent the estimated regression coefficients for each independent variable. They indicate the average change in the dependent variable associated with a one-unit change in the corresponding independent variable, holding all other variables constant.
    - **Intercept**: The estimated value of the dependent variable when all independent variables are zero.
    - **Categorical Variables (C(wave_KPI))**: These are dummy variables representing different categories of the wave KPI variable. The coefficients show the average change in SPLS when moving from the reference category (for example, when moving from waves from the back, which is 2, to waves from the front, which is 0).

- **Continuous Variables (wave_height, wind_speed, water_temperature, air_temperature)**: These coefficients indicate the change in SPLS associated with a one-unit increase in each respective variable.

In practical terms, it can be seen from the coefficients that the interaction between wave KPI being 2 and wave height has a significant negative impact on the shaft power per log speed. For example, consider a scenario where wave KPI equals 2 - tail waves, and the wave height increases by one unit. In such a scenario, the shaft power per log speed is expected to decrease by approximately 23.55 units. This negative coefficient represents that higher wave heights, particularly when the wave KPI is 2, lead to a reduction in shaft power relative to log speed (less power is required due to waves). In Fig 17, the same test can be seen for a new FPLS ratio (Fuel Per Log Speed). Here, the R-squared and the F-statistic results are even higher: 48,9% and 2.394e+04. In this ratio, when the wave height increases one unit and the waves hit the vessel from the back, a decrease of 5,79 units in the dependent variable can be seen as well.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   SPLS   R-squared:                       0.422
Model:                            OLS   Adj. R-squared:                  0.422
Method:                 Least Squares   F-statistic:                 1.824e+04
Date:                Thu, 25 Apr 2024   Prob (F-statistic):               0.00
Time:                        10:40:05   Log-Likelihood:            -9.1160e+05
No. Observations:              200018   AIC:                         1.823e+06
Df Residuals:                  200009   BIC:                         1.823e+06
Df Model:                           8
Covariance Type:            nonrobust
==============================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------------
Intercept                     87.7334      0.305    287.349      0.000      87.135      88.332
C(wave_KPI)[T.1]              11.4016      0.261     43.622      0.000      10.889      11.914
C(wave_KPI)[T.2]              15.4888      0.250     61.843      0.000      14.998      15.980
wave_height                   18.8711      0.089    211.912      0.000      18.697      19.046
C(wave_KPI)[T.1]:wave_height -12.4744      0.137    -90.988      0.000     -12.743     -12.206
C(wave_KPI)[T.2]:wave_height -23.5462      0.128   -184.648      0.000     -23.796     -23.296
wind_speed                     2.2984      0.021    109.503      0.000       2.257       2.340
water_temperature             -0.4415      0.034    -13.037      0.000      -0.508      -0.375
air_temperature                1.3126      0.032     41.451      0.000       1.251       1.375
==============================================================================
Omnibus:                    20489.008   Durbin-Watson:                   0.099
...
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Fig 16 - OLS test summary SPLS

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   FPLS   R-squared:                       0.489
Model:                            OLS   Adj. R-squared:                  0.489
Method:                 Least Squares   F-statistic:                 2.394e+04
Date:                Thu, 25 Apr 2024   Prob (F-statistic):               0.00
Time:                        12:09:54   Log-Likelihood:            -6.1153e+05
No. Observations:              200018   AIC:                         1.223e+06
Df Residuals:                  200009   BIC:                         1.223e+06
Df Model:                           8
Covariance Type:            nonrobust
==================================================================================================
                                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------------
Intercept                       25.5347      0.068    374.898      0.000      25.401      25.668
C(wave_KPI)[T.1]                 2.9670      0.058     50.885      0.000       2.853       3.081
C(wave_KPI)[T.2]                 4.3460      0.056     77.787      0.000       4.237       4.456
wave_height                      4.8312      0.020    243.191      0.000       4.792       4.870
C(wave_KPI)[T.1]:wave_height    -2.9931      0.031    -97.863      0.000      -3.053      -2.933
C(wave_KPI)[T.2]:wave_height    -5.7947      0.028   -203.699      0.000      -5.850      -5.739
wind_speed                       0.5317      0.005    113.545      0.000       0.522       0.541
water_temperature               -0.2392      0.008    -31.663      0.000      -0.254      -0.224
air_temperature                  0.1988      0.007     28.147      0.000       0.185       0.213
==============================================================================
Omnibus:                    33039.493   Durbin-Watson:                   0.102
...
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Fig 17 - OLS test summary FPLS

5.6 Data interpolation

Employing a data-driven approach, selecting data only where wave heights are below 1 m and wind speeds are below 2 m/s reveals near-calm water conditions, as illustrated in Fig 18. These data points represent the shaft power/fuel consumption required for different vessel speeds under non-severe meteorological conditions. This visualisation shows the area from Fig 12 - 13 where the dots were dark blue coloured, and is the first step towards a data-driven approach where the loads over the shaft power and fuel consumption generated by the weather can be subtracted.

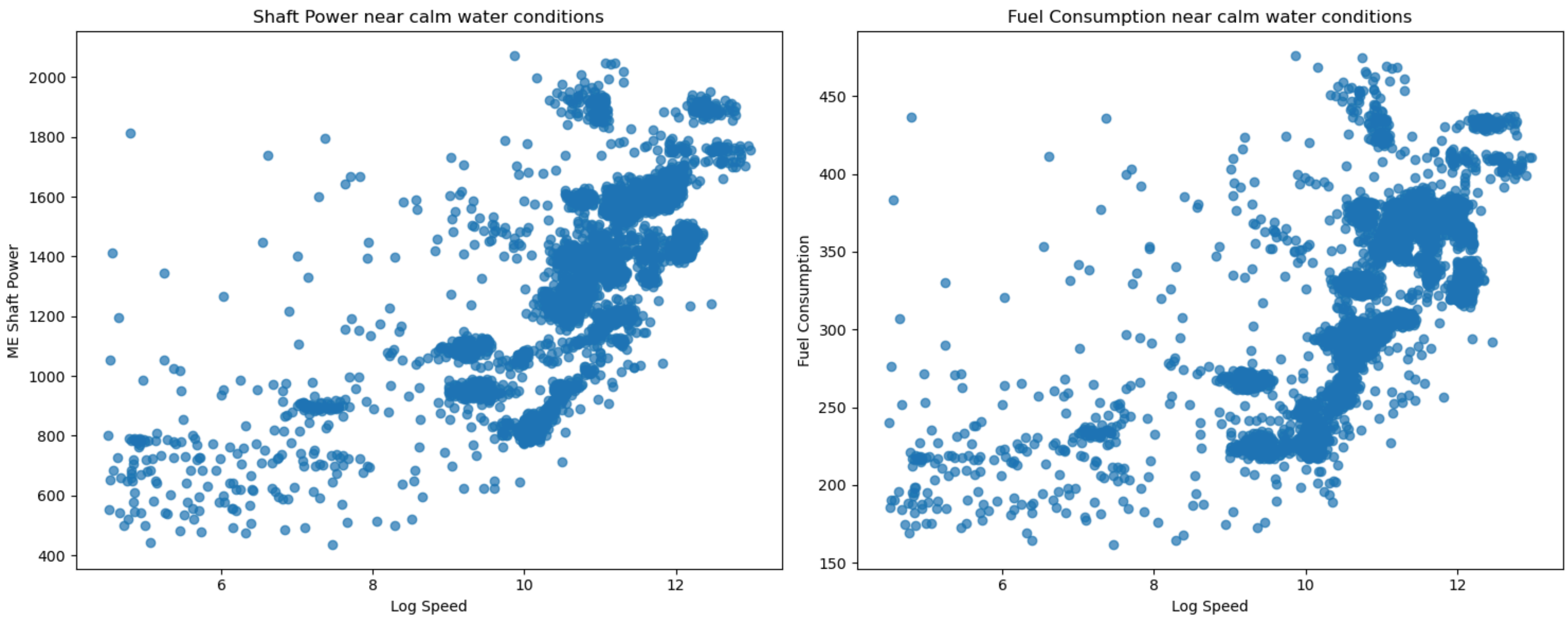

Fig 18 - Near calm water shaft power and fuel consumption required for each log speed

In the scatter plot representation of near calm water conditions, a polynomial curve is fit to the data points (see Fig 19). This is done using the NumPy Python library that supports numerical computing and has a module for polynomial operations. Polynomial operations are commonly used in curve fitting to approximate relationships between variables in data sets. A polynomial curve can represent the variations in power and fuel requirements across different speeds, providing a more generalised understanding of the relationship. By fitting a polynomial curve, it is possible to generate a line that gives the exactly required shaft power and fuel consumption for each log speed at ideal conditions. Fig 20 uses the same approach but in terms of fuel consumption.

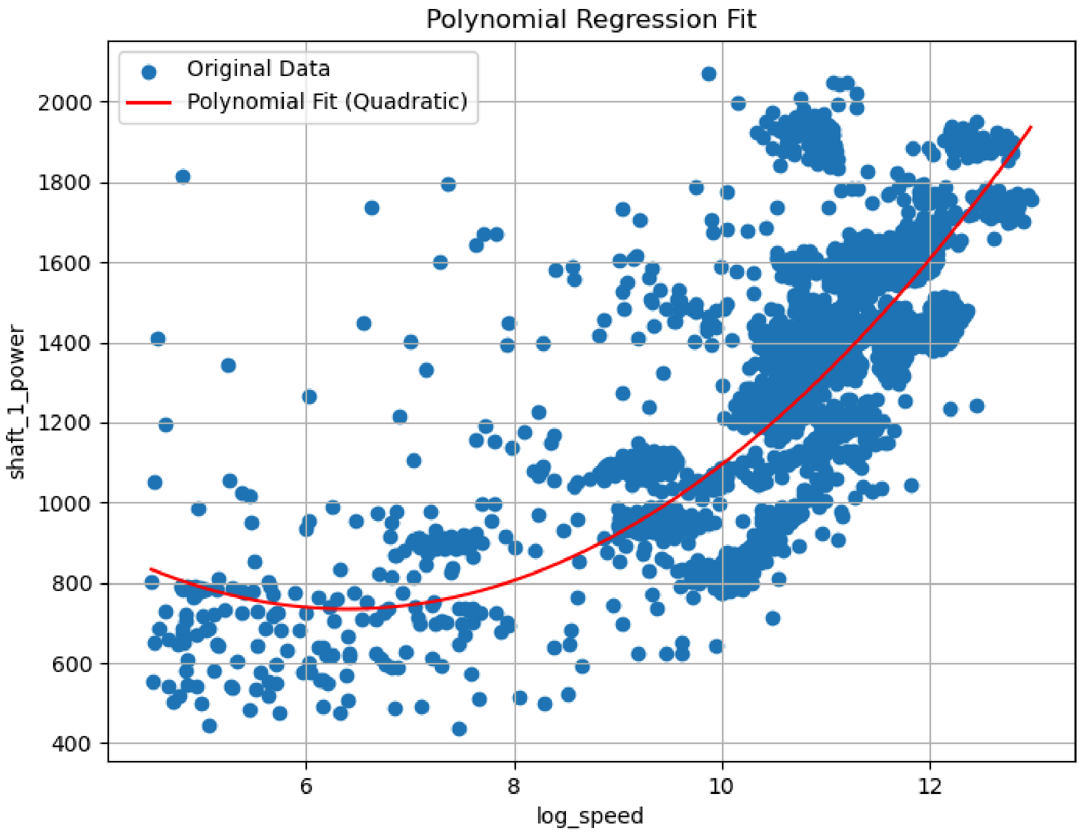

Fig 19 - Near calm water shaft power polynomial curve fit

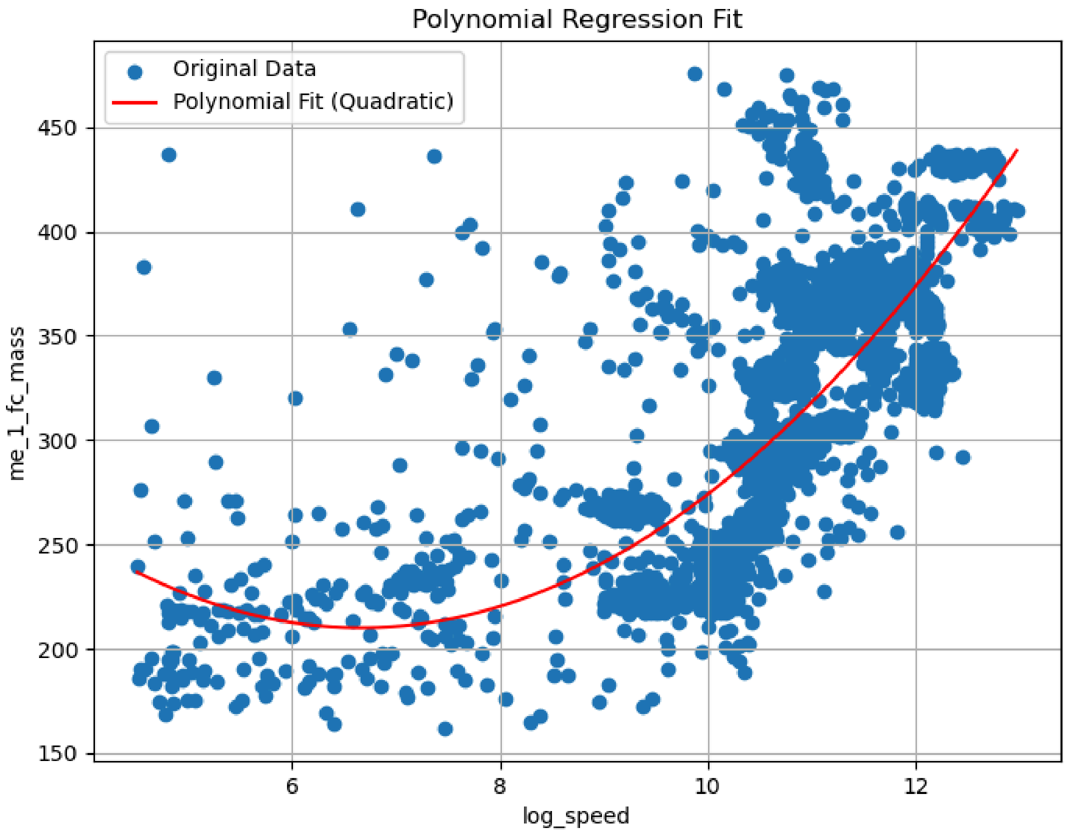

Fig 20 - Near calm water fuel consumption polynomial curve fit

After fitting the both polynomial curves, two pandas DataFrames are created. These DataFrames serve as structured tables containing the log speed values and the corresponding shaft power and fuel consumption values. See the example on Table 7. Another table is also created for the fuel consumption values.

log_speed	shaft_1_power
4.5	831.052598
4.6	820.897770
4.7	811.296730
4.8	802.249479
4.9	793.756016

...	...
12.6	1802.786194
12.7	1837.488233
12.8	1872.744060
12.9	1908.553676
13.0	1944.917080

Table 7 - Pandas DataFrame example near calm water required shaft power for each log speed

Hence, we have a set of data that represents various sailing speeds and their corresponding shaft power/fuel usage values in near calm water conditions. Now, imagine we want to estimate how much shaft power or fuel consumption a ship would need for each speed in a larger dataset, but we don't have the exact values for those speeds.

To do this, we can use our reference table as a guide. For each speed point in our dataset, we look at the nearest speed value in our reference table (Table 7) and find the corresponding shaft power value or fuel consumption. This gives us an estimate of how much shaft power or fuel would be needed for that speed based on our reference data. We repeat this process for all speed points in our dataset, adding these estimated shaft power values to our original dataset in new columns. This way, it is possible to compare the actual shaft power values with the estimates to see if there's any overconsumption – meaning the ship is using more power or more fuel than expected due to factors like weather conditions, such as high waves or strong wind speeds. 4 new columns are aggregated to the large dataset: interpolated_fuel_consumption, fuel_overconsumption, interpolated_shaft_1_power and shaft_overconsumption.

5.7 Model development

Every row in the dataset has the additional shaft/fuel consumption column calculated, which can be used as a target variable in a ML model. With this approach, the model can therefore learn many different combinations and scenarios where the weather is affecting vessel operations and:

1) can provide real-time insights, 2) can leverage the trained model as a predictive tool and, 3) will learn from experience as more data is acquired under different sailing conditions.

An overview of the process is shown in Fig 21:

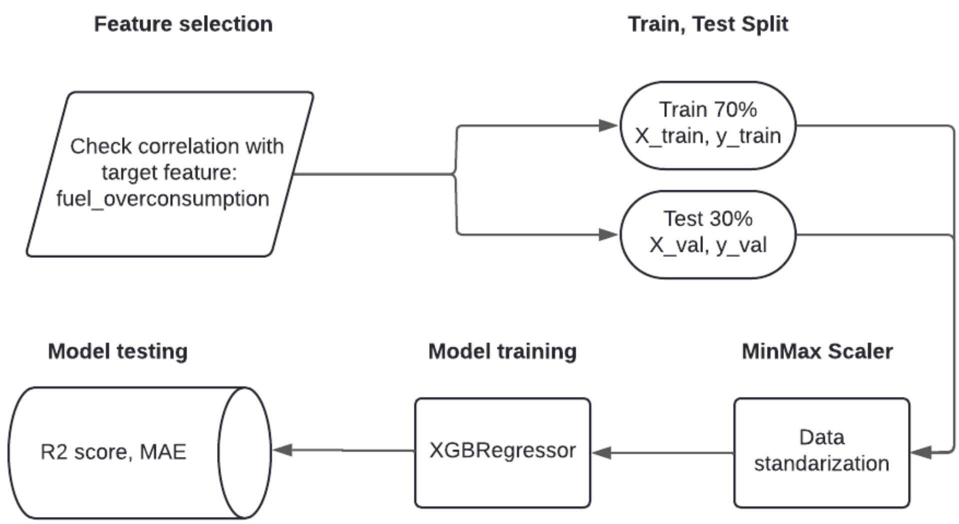

Fig 21 - Model training and testing process overview

5.7.1 Fuel over consumption model

In the process of training the ML model the selection of features holds significant importance. To determine which features are most relevant, the correlation among features and the target variable is analysed. The highly correlated features are then prioritised for inclusion in the ML model training process (Zipporah, 2021). In the case of our data, when analysing these correlations: shaft_1_power, me_1_rpm, draft_fwd, wave_height, wave_period and log_speed are the selected features. The correlation coefficients range from approximately 0.35 to 0.65, being the shaft power the most correlated variable. The log_speed variable is also negatively correlated with a coefficient of -0.34.

A new data frame called “data_to_predict” is created. In this case, the data frame is formed by: 'fuel_overconsumption' (target variable), 'shaft_1_power', 'me_1_rpm', 'draft_fwd', 'wave_height', 'wave_period' and 'log_speed'. See Table 8 where an example of the independent and the dependent variables can be seen.

Relevant to mention, features such as wind_speed are excluded, although it shows a positive correlation with the target variable. Including wind_speed and wave_height at the same time may introduce redundancy -or multicollinearity- in the model. Multicollinearity occurs when two or more independent variables in a regression model are highly correlated with each other (Hayes, 2024). In this case, both wave_height and wind_speed are variables that describe aspects of weather conditions, and they are likely correlated since wind speed influences wave height. When highly correlated variables are included in a regression model, it can be difficult for the model to determine the individual effects of each variable on the target outcome (in this case, fuel overconsumption). This can lead to instability in the model's coefficients and reduce its predictive accuracy. Excluding one of the correlated variables helps mitigate multicollinearity and improves the model's interpretability and performance.

Independent variables				**Dependent variable or target variable**
X_1	**X_2**	**…**	**Xn**	**y**
‘shaft_1_power’	‘me_1_rpm’		N independent variables	‘fuel_overcosumption’

Table 8 - Example of independent variables (X) and target variable (y)

Once the dataset is defined, it is divided into training and validation sets, ready for model training and evaluation. The independent variables (features) related to sailing conditions and engine parameters are stored in variable X, while the dependent variable (target) representing fuel overconsumption is stored in variable y. The dataset split is performed using the train_test_split function, allocating 70% of the data for training (X_train, y_train) and 30% for validation (X_val, y_val). Splitting the dataset into training and validation sets is done to assess the performance of the machine learning model. The training set is used to train the model on historical data, allowing it to learn patterns and relationships between the independent variables (features) and the dependent variable (target). The validation set, which contains unseen data, is then used to evaluate the model's performance. By comparing the model's predictions on the validation set to the real values, it is possible to assess how well the model makes predictions on new and unseen data (Brownlee, 2020). This process helps ensure that the model can accurately predict fuel overconsumption in real-world scenarios.

Before training the model, the dataset is standardised by rescaling the distribution of values. This process involves transforming the data so that it fits within a specific range or distribution. Here, the MinMaxScaler() function is used, which scales each feature to a specified range, typically between 0 and 1. This is an important step and it ensures that all features have the same scale, preventing any one feature from dominating the others during model training. This can lead to more stable and accurate model performance (Gogia, 2019). By rescaling the distribution of values, the dataset is more suitable for modelling, improving the robustness and interpretability of the machine learning model.

5.7.2 XGBRegressor

The selected model is the XGBRegressor. XGBoost (Extreme Gradient Boosting) is an open source library and a powerful and efficient implementation of gradient boosting machines, known for its high performance in various machine learning tasks, particularly in tabular data problems (Brownlee, 2021). The XGBRegressor is specifically designed for regression tasks, making it suitable for predicting continuous numerical values.

Gradient boosting refers to a class of ensemble machine learning algorithms. Ensembles are constructed from decision tree models. Trees are added one at a time to the ensemble and fit to correct the prediction errors made by prior models. This is a type of ensemble machine learning model referred to as boosting. Models are fit using any arbitrary differentiable loss function and gradient descent optimization algorithm. This gives the technique its name, “gradient boosting,” as the loss gradient is minimised as the model is fit, much like a neural network (Brownlee, 2021). Additionally, XGBoost includes advanced regularisation techniques to prevent overfitting and is computationally efficient and scalable, making it suitable for handling large datasets with a large number of features.

In the case of this project, the XGBRegressor model was initialised using default parameters. The model was trained on the training dataset (X_train and y_train) prepared before. The fit() method was used for this step. During training, the model learned the relationships between the input features (X) and the target variable (y) to make accurate predictions. After training the model, the coefficient of determination (R^2 score) was calculated to evaluate the performance of the model to the training data. The R^2 score indicates the proportion of the variance in the target variable that is explained by the model. A higher R^2 score (closer to 1) suggests a better result (Ihechikara,).

Once the model was trained, it was applied to make predictions on the very same training set (X_train). These predictions were compared with the actual target values to evaluate the model's performance on the training data. The MAE was therefore calculated to quantify the average absolute difference between the predicted values (y_pred_train) and the actual values (y_train).

Similarly, the trained XGBRegressor model was tested to make predictions on the validation set (X_val). These predictions were compared with the real target values to evaluate the model's performance on new and unseen data. The MAE was also calculated to quantify the average absolute difference between the predicted values (y_pred) and the real values (y_test).

The results are shown in Table 9:

Metric	**Value**	**Explanation**
R^2 score	0.9921	The score indicates that the XGBRegressor model explains 99% of the variance in the target variable based on the features included in the model. This high R^2 score suggests that the model fits the training data significantly well and captures most of the variability in the target variable.
MAE (Training set)	3.39	A MAE of 3.39 on the training set indicates that, on average, the absolute difference between the predicted and actual values is 3.39 units. This low MSE suggests that the model's predictions closely match the actual values on the training data, further supporting the high R^2 score and the model's good performance on the training set.

MAE (Test set)	13.40	The MAE of 13.40 on the test set indicates that, on average, the absolute difference between the predicted and actual values is 13.40 on unseen data (test set). While this MSE is higher than the MSE on the training set, it is still relatively low, suggesting that the model generalises well to unseen data. However, it's important to note that the MAE on the test set is slightly higher than on the training set, indicating a small drop in performance when the model is applied to new data.

Table 9 - XGBRegressor results

In practical terms, MAE provides valuable insight into the accuracy of the model's predictions for the fuel overconsumption variable. For example, if the MAE is 3 units, it means that, on average, the model's predictions deviate from the actual fuel overconsumption by 3 units. These results could be increased by 1) adding more new features depending on data availability, and, 2) collecting more data to train the model on a higher number of different scenarios, preparing it for better performance on new unseen data. Remember that this dataset only contains data from around half a year, or less, leaving out important seasons as it could be winter.

Fig 22 displays the actual values versus the predicted values for the validation set. Each point on the scatter plot represents a data point from the validation set, where the x-coordinate represents the actual value and the y-coordinate represents the predicted value. The red dashed line represents the ideal scenario where the predicted values would perfectly match the actual values. Ideally, all points should fall along this red dashed line, indicating perfect predictions. In this plot, deviations from the red dashed line indicate discrepancies between the actual and predicted values. The distribution of points around the red dashed line provides insight into the accuracy and precision of the model's predictions.

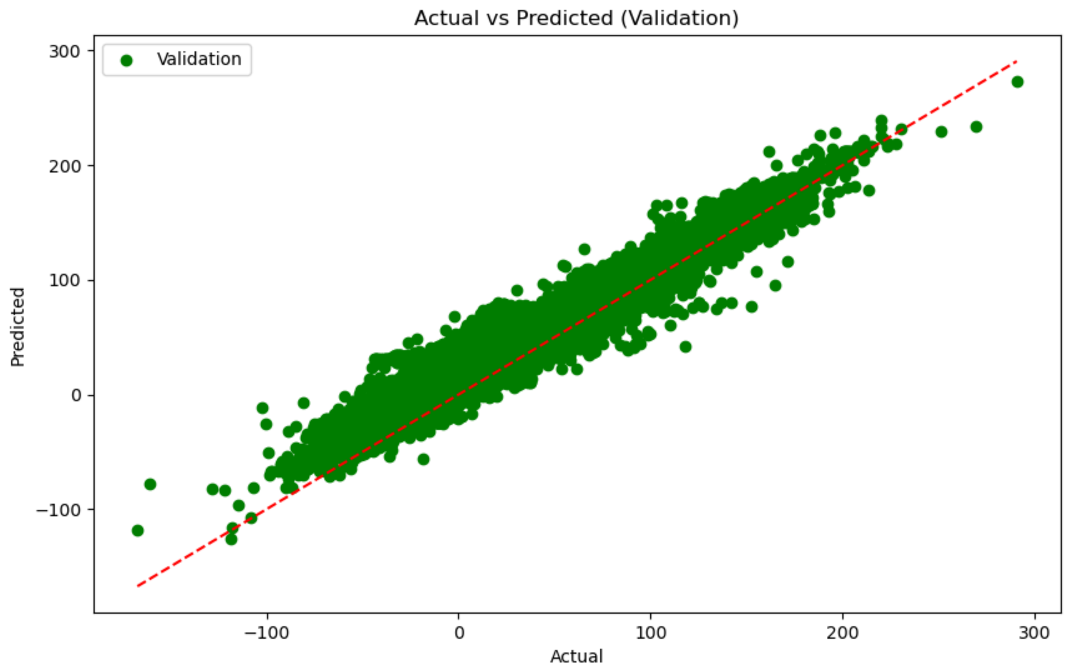

Fig 22 - Actual vs Predicted values validation set

Finally, Fig 23 represents a Streamlit application, providing a simple way to present the solution to stakeholders and discuss what should be added in the interface, as well as offering a simulation of a practical example in a real world scenario. In this case, the left column shows information about the weather in current sailing conditions, where an accumulation of extra fuel consumed due to weather effects is calculated. In the middle column, the real fuel consumption (blue line) vs the ideal fuel consumption (red line) are compared, as well as a map that provides by GPS coordinates the route of the vessel during the last 6 months. The column on the right side contains text boxes where the input parameters for the model are inserted, giving out predictions. The application could be improved using APIs to refresh the data automatically and adding new plots, but as mentioned in the *3.6 Deployment* section, this is not a priority and has been limited to a simple simulation for the current project.

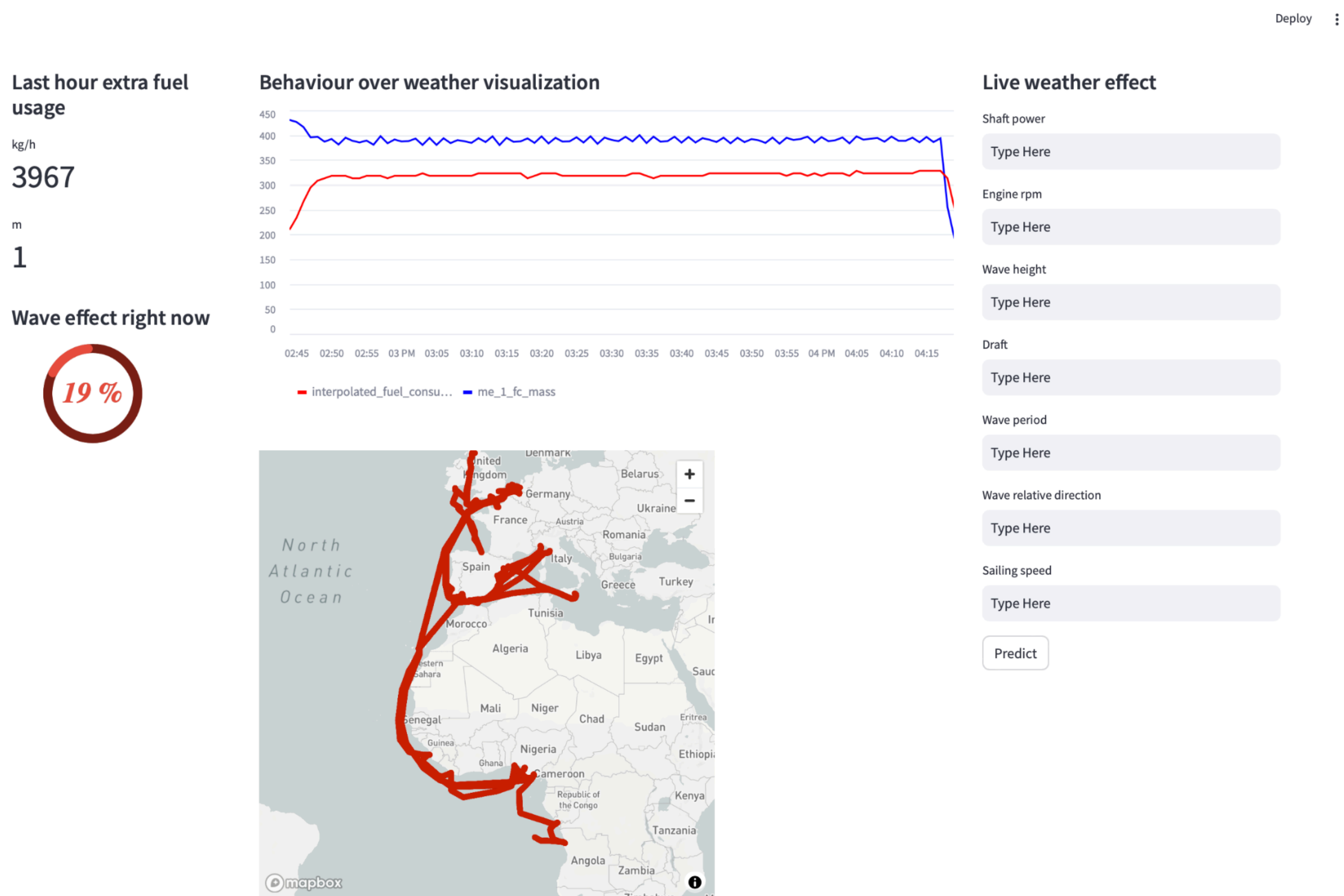

Fig 23 -Streamlit interface example

6. Discussion

In general, different engine behaviours or operating zones can be found across different meteorological situations. The ship speed decreases significantly for the same engine power, under strong winds and bigger waves. The same effect was found for the fuel consumption. Applying the polynomial curve over the near calm water operating zones allowed to generalise how the engine should behave on ideal sailing estate, interpolating these values to the whole dataset and calculating overexceeds, as is the case of extra fuel consumption. Finally, the ML has taken this feature as a target, allowing it to create a weather effect prediction tool.

Translating this into business objectives, quantifying the impact of weather conditions on fuel consumption opens new avenues for fleet owners. Considering future development, the current solution can serve as a foundation for advancing into more complex projects and applications, as is the case of weather routing systems, which involves selecting ship routes based on weather forecasts by the leverage of ML models, and contributes to more efficient sailing and less CO_2 emissions. Additionally, the quantification of weather loads on a vessel can contribute to the PdM solution that the company is currently developing, where SFOC values can be recalculated, and assess engine degradation over time. Currently, the approach that the company uses in order to cancel weather noise relies on filtering the data according to the beaufort scale. If the beaufort level is lower than 4, they will select this data and use it for the PdM solution, limiting to only scenarios where this weather conditions occur. Contrary, if the weather effect can be tackled over all the scenarios, the SFOC values can be recalculated and there is no need of filtering.

Regarding limitations throughout the project, domain expertise has played an important role in understanding the data and aligning it with project goals. Without domain expertise, the task of interpreting the data accurately and selecting pertinent features would be significantly more challenging. However, thanks to the commitment and collaboration of personnel from the company, this issue has been counterweighted. Due to the given timeframe, practicality has been prioritised over perfection, where the experience of working in a real environment has contributed to seeing the relevance of approaching a task with a realistic mindset. This approach ensured that resources were utilised efficiently and that the project remained focused on delivering tangible results within the allocated time period. Furthermore, a big percentage of learning within this collaboration comes from the experience of meeting colleagues and learning from them in the company.

In terms of future work and achieving better results, the accumulation of new data will enrich the repository. Thereby, if more people with the required knowledge from the organisation are allocated to further working with this, their accumulated knowledge through years, combined with the collection of new data, can significantly improve the accuracy of quantifying the exact effects of weather conditions on sailing.

Additional ML models can also be developed and cross-validated. DL models could enhance accuracy and provide better results, but this consideration involves factors such as how often the model needs to be trained. ANN, recurrent neural network (RNN) or long-short term memory (LSTM) architectures have been used across industry researchers, but they are computationally less efficient and require more training time. However, they might work better capturing non-linear patterns in the data.

7. Conclusion

It is expected that the shipping industry will undergo an accelerated development, as it is already visible that the industry is pushing forward to the science of data and more sophisticated maintenance approaches. Even though the field of PdM is still in a very early phase, forward thinking organisations must think about big data and artificial intelligence as key drivers for enhancing their operations. However, this transition might occur slowly and organically, as many fleet owners manage their assets in a traditional way (Jimenez et al., 2020).

This project represents a contribution to a big project based on PdM in collaboration with a company from the shipping industry. Relating to the project's sub-question derived from the main research-question, the aim was to **analyse how the shaft power and fuel consumption variables were affected by weather loads**, and this was accomplished by identifying the vessel's ship speed power performance, also presented as engine behaviour or different operating zones. This helped to create a polynomial curve for the values that should be expected when sailing in calm waters, allowing for calculating a new feature of fuel overconsumption. With this, an XGBRegressor model was trained and tested, showing good performance and satisfactory results.

While the model shows the potential to serve as a predictive tool, there are yet some factors that should be considered. This model was trained only in data representing 6 months of the year, and it could be a limitation when making predictions in new scenarios. Although the polynomial curve demonstrates a generalisation of good sailing conditions, there is still some variability that should also be considered. In this vein, in terms of future work, assessing the performance and accuracy of the model in real scenarios should be the first task, accompanied by refining the logic behind the creation of the near-calm water conditions values. This could be done leveraging data from other vessels, and analysing their engines behaviour, to find patterns.

In conclusion, the significance of this work demonstrates that:

- Weather effects on the shaft power and fuel consumption can be tackled analysing the engine behaviour over different weather situations.
- Implementing ML can help extend this solution by developing more sophisticated solutions, serving as a predictive tool.
- The SFOC, used for the PdM solution, can be noised-out having the values for these parameters when sailing in calm waters.

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