OPERATIONAL DATA ANALYSIS TO AID THE OPTIMIZATION OF RETROFIT SOLUTIONS WITHIN '*RETROFIT55*' FRAMEWORK

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ABSTRACT

The RETROFIT55 EU project aims to develop and demonstrate energy-saving solutions able to reduce the fuel consumption of waterborne transport by at least 35% before 2030 compared to 2008, with particular focus on retrofits. In the current paper two key areas of this project are presented. The first one concerns the operational data analysis of the bulk carrier case study and the use of the data to derive useful conclusions and setup of the subsequent hydrodynamic optimization studies that will follow. The second one focuses on the operational optimization measures. Specifically, the preliminary assessment of the vessel's hydrodynamic performance is presented, using an appropriate Key Performance Indicator (KPI) and aiming at the identification of the effect of maintenance actions. This analysis is a first step towards a more advanced method for the hull & propeller condition monitoring that will be based on data-driven models. Therefore, key elements and steps needed for the development of the Machine Learning (ML) models are briefly highlighted. Lastly, the next steps of hydrodynamic optimization are discussed.

KEYWORDS

ship energy efficiency, retrofitting, hydrodynamic optimization, operational data, data analysis.

1. INTRODUCTION

Legislative proposals within the EU's "Fit for 55" package targeting the reduction of waterborne transport emissions will assess emissions reductions based on operational data collected from the EU's MRV regulation framework, while for global maritime shipping with the use of IMO Carbon Intensity Indicator and Data Collections System (DCS). Within this context EU HORIZON has funded an Innovation Action project 'RETROFIT55' run by a diverse consortium of experts from Industry and Academia.

(Iafrati et al 2024).

The current paper presents an initial analysis related to two key areas of the problem. The first one concerns the retrofitting solutions for improving the ship's hydrodynamic design. The aim is to utilize ship operational data to focus on realistic loading and weather conditions. More specifically, to explore retrofitting solutions for improving the ship's hydrodynamic design, the effect of multiple different factors on the ship's hydrodynamic performance needs to be investigated. A systematic and efficient method for studying the relationship between multiple input variables and the output variables is known as Design of Experiments (DoE, Renzsch & Thies 2023, Ahmed et al. 2023). To conduct a DoE aiming to the ship's hydrodynamic optimization, detailed simulations are required. These simulations should be done in realistic conditions in accordance with the ship's actual operation. Information about the operational parameters can be derived from the measured data obtained either from noon reports or from an automated logging system. Thus, operational data analysis is required to aid the exploration of retrofitting solutions in the DoE framework. The second area which the initial assessment of operational data will contribute is related with the development of a hull and propeller condition monitoring tool based on data-driven models employing ML methods. Therefore, a preliminary assessment as well as the planned steps will be also described.

Section 1 describes the dataset and the available parameters for the examined ship, while Section 3 focuses on a comparative study between the several sources of acquiring data. Section 4 examines the identification of loading conditions through the analysis of operational data. Section 5 presents the preliminary assessment of the hull condition and highlights the roadmap for the development of the monitoring system. Finally next steps and basic conclusions of this study are discussed.

2. CASE STUDY SET UP

A dataset generated by the high frequency monitoring system on-board the examined bulk carrier has been provided by Laskaridis Shipping Co. Ltd (LASK). The dataset spans two years (from February 2021 to February 2023) and has one minute sampling period, so it consists of 1,064,161 datapoints; it contains 559 parameters, some of which correspond to direct measurements from onboard sensors, other from the weather provider, while some are developed for internal purposes. Specifically, parameters built by the DAQ providers aiming to provide their own reports to the shipping company have been omitted because their exact definition is unknown. Similarly, parameters developed to treat outliers have been left out, since each data analyst uses his own methods for this operation. As a result, a dataset with 268 parameters has been derived for analysis. Table 1 presents principal characteristics of the examined ship.

Table 1: Main characteristics of the examined ship

Length overall	229.00 m
Length between perpendiculars	225.50 m
Breadth, moulded	32.26 m
Depth, moulded	20.05 m
Summer load line draught, moulded	14.45 m
Deadweight at summer load draught	80996.1 t
Main Engine	HYUNDAI-MAN B&W - 6S60ME-C8.5
Maximum continuous rating (MCRME)	9930 kW x 90.4 rpm

Weather data from third-party providers have an actual time resolution of one hour, which is then changed to one minute to match the rest of the data. Available parameters include sea temperature, air pressure and temperature, wind speed and direction, total current speed and direction. More importantly, parameters regarding wave, wind-wave and swell characteristics have been provided, together with explanations listed in Table 2.

Table 2: Explanations of wave parameters

Significant wave height	Spectral approximation of the observed mean wave height of the largest 33% of the waves within a 20-minute window.
Max wave height	Mean of 1% highest waves or 1.67Hs according to deep water Rayleigh distribution.
Mean wave direction	Mean direction where waves are arriving from. Mind the combination of multiple wave trains.
Mean wavelength	On deep water (>500m) the mean wavelength can be computed as 1.56T2. Account for the dispersion relation on shallow water.

In addition to the high-frequency data, LASK has also provided a noon report dataset for the same two-year period, consisting of 739 datapoints. Noon reports are prepared daily, include fewer parameters than the automated logging system, and the values they provide are less accurate.

3. COMPARISON OF SPESIFIC HIGH FREQUENCY AND NOON REPORT PARAMETERS

When examining the high-frequency dataset, it became clear that some variables were missing or invalid over certain periods. In particular, the draft and ME FOC sensors produced faulty values for some time, and data from weather providers were unavailable during the first year of the sampling period. Automated logging is certainly more reliable due to the higher frequency and accuracy of the measurements, but noon report information is available throughout the examined period and should therefore be considered in cases where high frequency recording is missing. Before deciding to incorporate noon reports, it is worth evaluating them against their high-frequency counterparts when available. To enable comparison, noon report draft and weather variables are filled in per minute based on their daily values to have the same time resolution as the high-frequency data.

The mean draft is calculated by averaging the fore and aft draft measurements. High frequency draft recording is valid from February to November 2021. In Figure 1 mean draft values from noon reports during this period are plotted against the corresponding mean draft derived from the high-frequency sensors. The points are mostly clustered around the 45-degree line, confirming the agreement between the two recording methods. The horizontal lines occurring in the plot indicate the increased variability captured by automated draft recording as opposed to the noon report measurement, which is performed manually once per day. A histogram of the difference of the mean drafts derived by the two sources is shown in Figure 2. The mean difference of –0.54 m between the two sources amounts to bias, whereas the standard deviation of 1.41 m is due to high frequency recording variance.

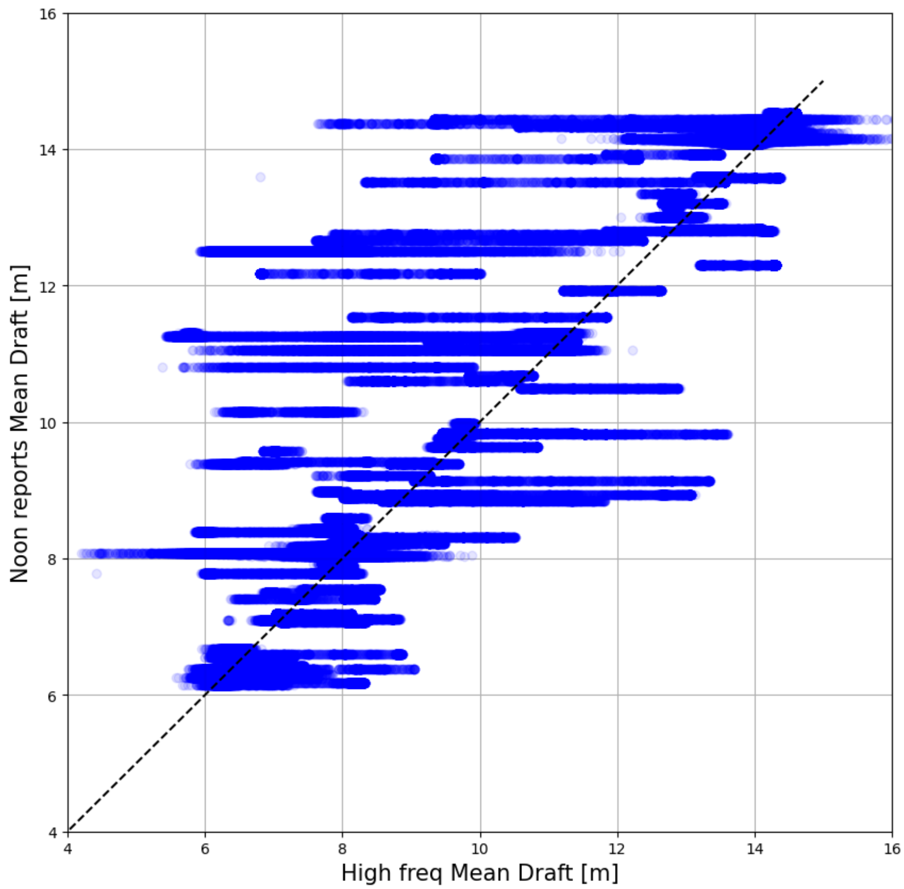

Figure 1: Comparison of high frequency and noon reports mean draft.

Data from a weather provider are available from April 2022 to February 2023. Since wind and current data are obtained from the on-board monitoring system, only wave parameters need further examination. In Figure 3 sea height values from noon reports during this period are plotted against the corresponding significant wave height obtained from a weather provider. The clustering of the points around the 45-degree line verifies that the two recording methods agree; horizontal lines are again evident because of the higher sampling frequency of the weather provider data (per hour) compared to the noon reports (per day). In Figure 4 a histogram of the difference of the two wave height parameters is shown; a mean of -0.11 m and a standard deviation of 0.91 m are calculated.

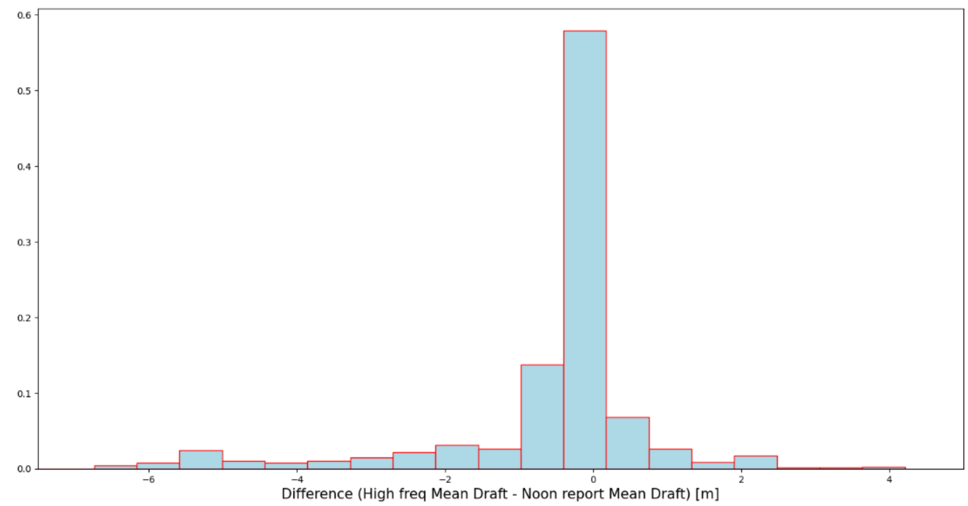

Figure 2: Histogram of high frequency and noon report mean draft difference.

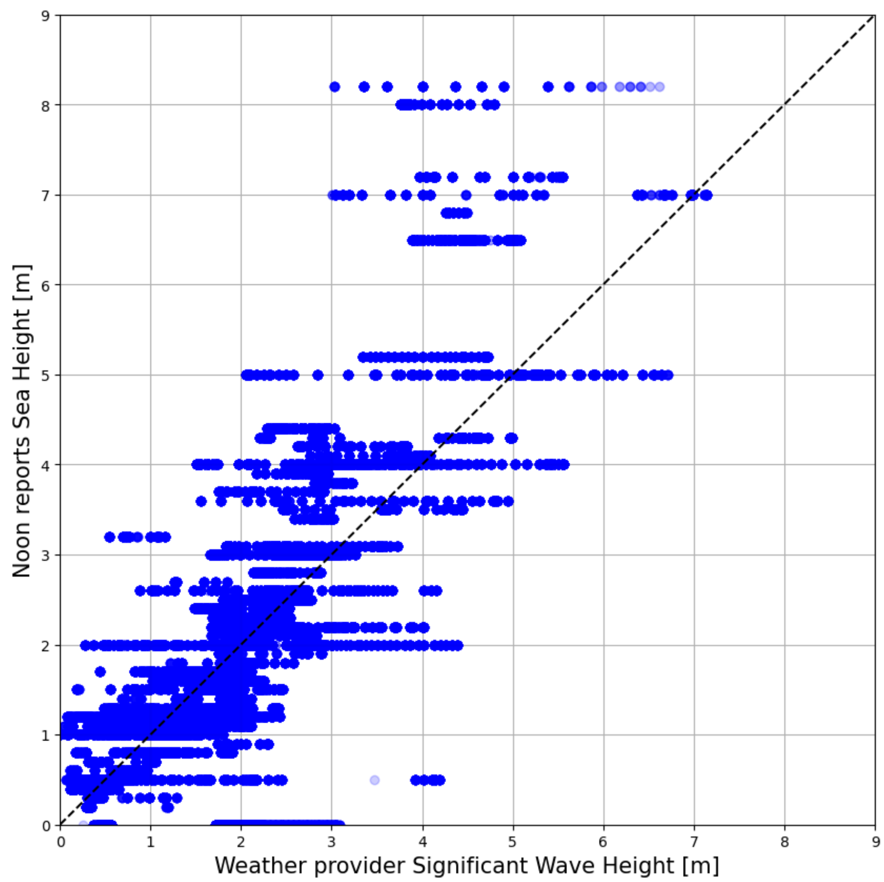

Figure 3: Comparison of high frequency and noon reports wave height.

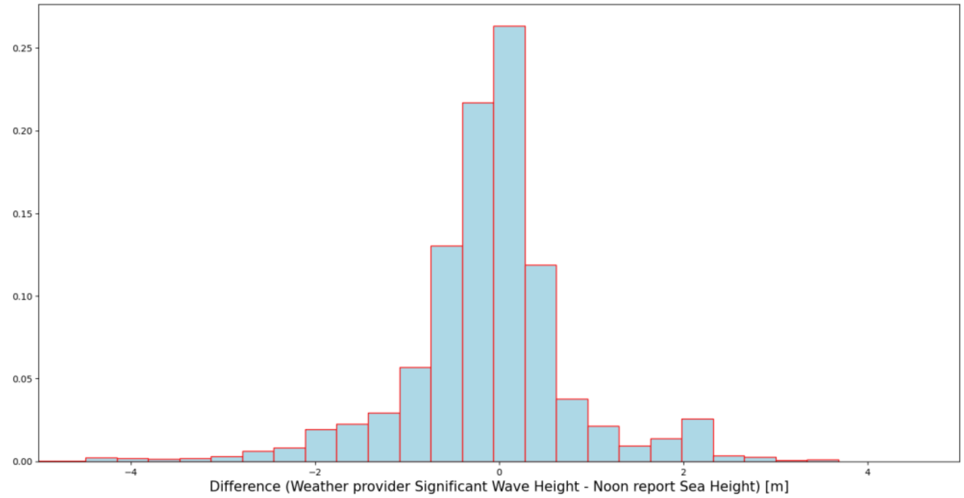

Figure 4: Histogram of high frequency and noon report wave height difference.

The results of the above comparative analysis validate the use of noon report draft and wave height data, instead of their high frequency counterparts, to remedy the data gaps.

A comparison is then made between three different vessel speed parameters: the first two are STW and SOG from high-frequency recording and the third is from noon reports. In Figure 5 the distributions of the three speed parameters are superimposed over each other, creating an overlaid histogram. Here, it is worth observing that the noon reports values lie close to SOG, while there is a noticeable deviation from STW, which receives higher values overall, because of sea current. Hence, the difference between SOG and STW is used to determine the sea current speed, which has a mean of -0.81 kn (STW>SOG) and a standard deviation of 1.06 kn, and its histogram is shown in Figure 6.

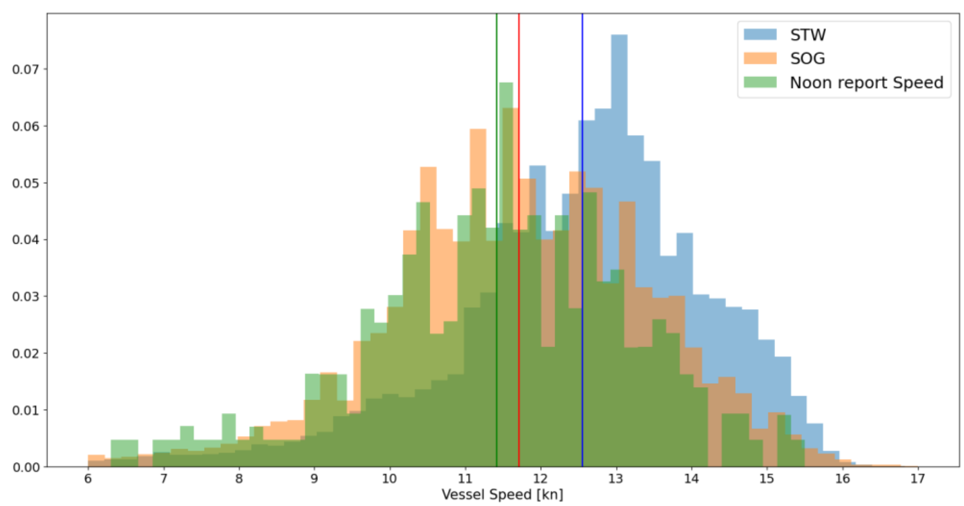

Figure 5: Overlaid histogram of STW, SOG and noon report speed.

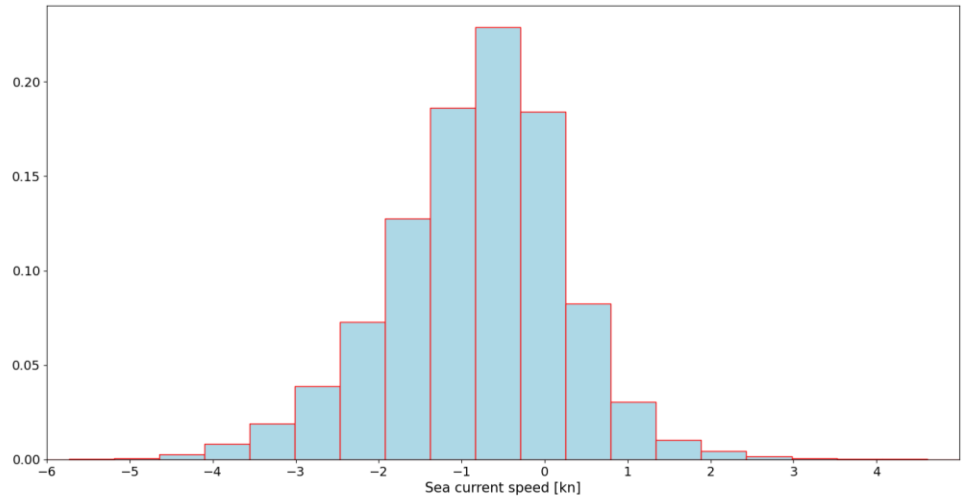

Figure 6: Histogram of sea current speed.

Another useful tool for exploring the ship's operation is to project its path on the world map by simply superimposing the GPS longitude and latitude signals on the map, as shown in Fig. 7. This helps identify the routes followed by the ship during the two-year recording period, information essential for implementing physics based or data driven weather routing.

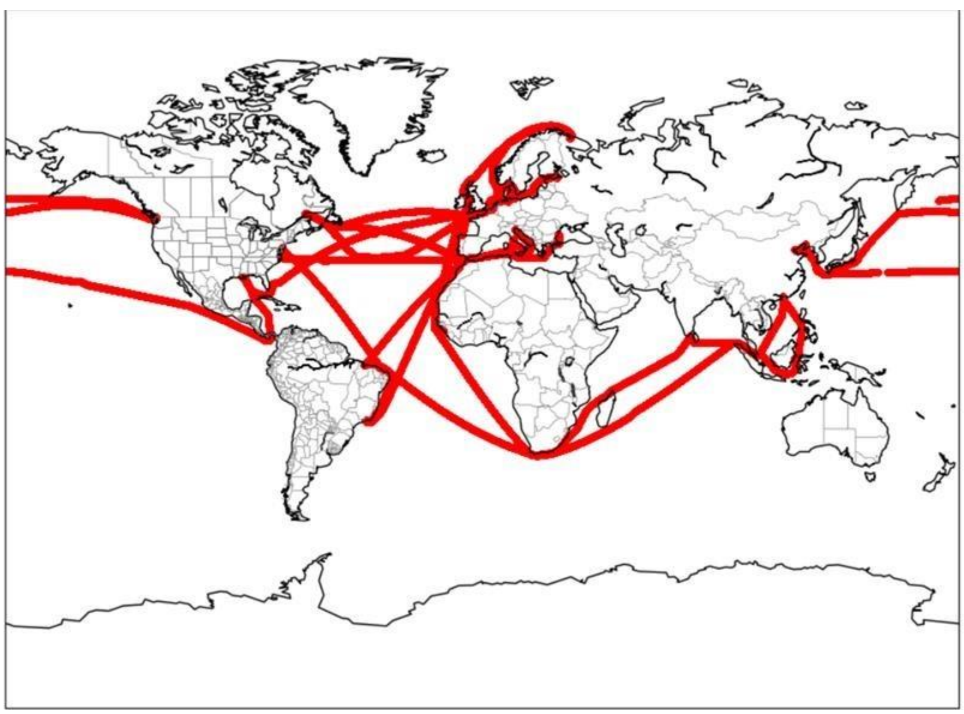

Figure 7: Projection of the ship's path on the world map.

4. IDENTIFICATION OF LOADING CONDITIONS

Proceeding with the data analysis, the draft distribution is examined revealing certain loading conditions the vessel was in during the reporting period. To exclude port calls, only data points with STW over 6 knots are considered. In Figure 8 the distribution of the mean draft is shown, which appears to be multimodal; the four peaks protruding near the values of 6.3 m, 8.1 m, 13.2 m and 14.3 m correspond to four discrete loading conditions: two laden and two ballast. The draft range of each loading condition, as listed in Table 3, is determined by the spread of the distribution around these peaks. Additionally, the trim is calculated by subtracting the aft from the fore draft measurement. In Figure 9 the histogram of trim is shown, indicating that the trim's distribution is bimodal; the peak near –0.2 m relates to the two laden conditions whereas the peak near –2.8 m relates to the two ballast conditions, as demonstrated in Figure 10.

Subsequently, each loading condition is reviewed separately by examining the respective trim and STW distributions. As a result, Table 4 is derived, where mean values and ranges for the mean draft, trim and STW are reported. This way the suggested operational range is obtained, to be considered for detailed simulations in the DoE process.

Table 3: Draft range per loading condition

Loading condition	Type	Draft range
1	Laden	TM>13.5 m
2	Laden	12 m<TM<13.5 m
3	Ballast	6 m<TM<6.5 m
4	Heavy ballast	7.75 m<TM<8.5 m

Table 4: Mean value and range for mean draft, trim and STW per loading condition

Loading condition	TM (m) Mean	TM (m) Range	Trim (m) Mean	Trim (m) Range	STW (kn) Mean	STW (kn) Range
1	14.24	[13.5, 14.5]	-0.17	[-0.5, 0]	12.24	[9, 15]
2	13.13	[12, 13.5]	-0.17	[-0.5, 0]	12.51	[11, 15]
3	6.31	[6, 7]	-2.81	[-3.5, -2]	12.92	[9, 16]
4	8.10	[7.75, 8.5]	-2.03	[-3, -1.5]	12.65	[9, 16]

5. IDENTIFICATION OF MAINTENANCE ACTIONS USING KPI AND BRIEF DISCUSSION ON DATA-DRIVEN MODELS

The accumulation of micro- and macro-organisms on underwater structures is known as "marine fouling" and has a huge impact on the efficiency of the shipping industry. Marine fouling on a vessel leads to increased surface roughness which in turn increases viscous drag and decreases the inflow speed at the propeller (Carchen & Atlar 2020); this makes the vessel less efficient when travelling through water, thus resulting to increased fuel consumption and emission of greenhouse gases. Algae, slime and seaweed growing abundantly on a hull constitute the soft (non-calcareous) fouling, that induces up to 20% powering penalties;

heavy (calcareous) fouling consists of barnacles, mussels and mollusks adhering to the vessel's surface, and can lead to an increase in power of more than 85% (Bressy & Lejars 2014). As a countermeasure, ships are drydocked periodically, and anti-fouling paints are applied on the hull to impede the adherence of marine organisms. Additionally, hull cleaning and propeller polishing is performed either while the ship is berthed (underwater hull cleaning) or in dry dock, using various devices (e.g., rotary brushes, water jet technology, ultrasonic technology, laser technology) to remove biofilm and calcareous formations (Song & Cui 2020).

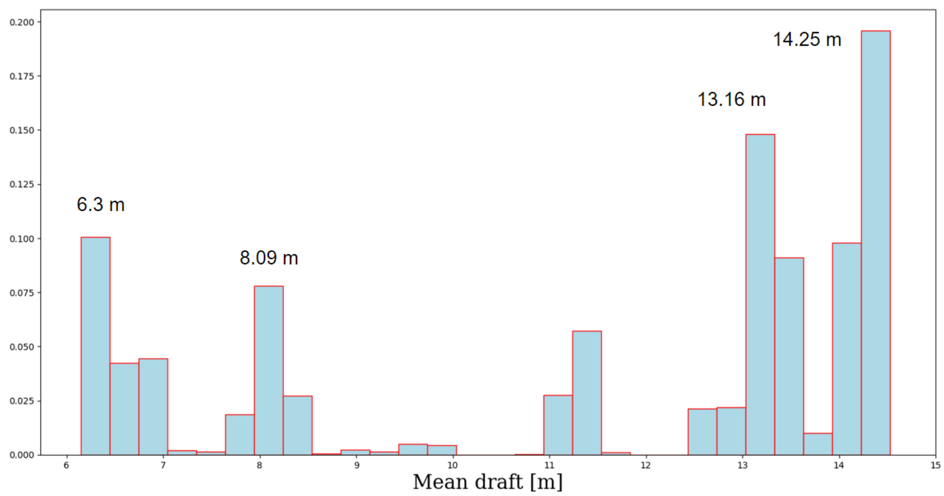

Figure 8: Histogram of the mean draft and corresponding loading conditions.

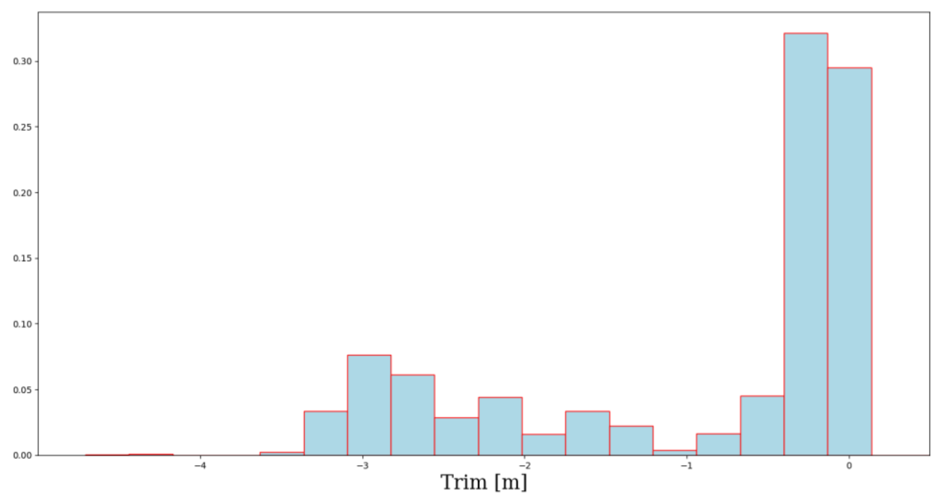

Figure 9: Histogram of the trim.

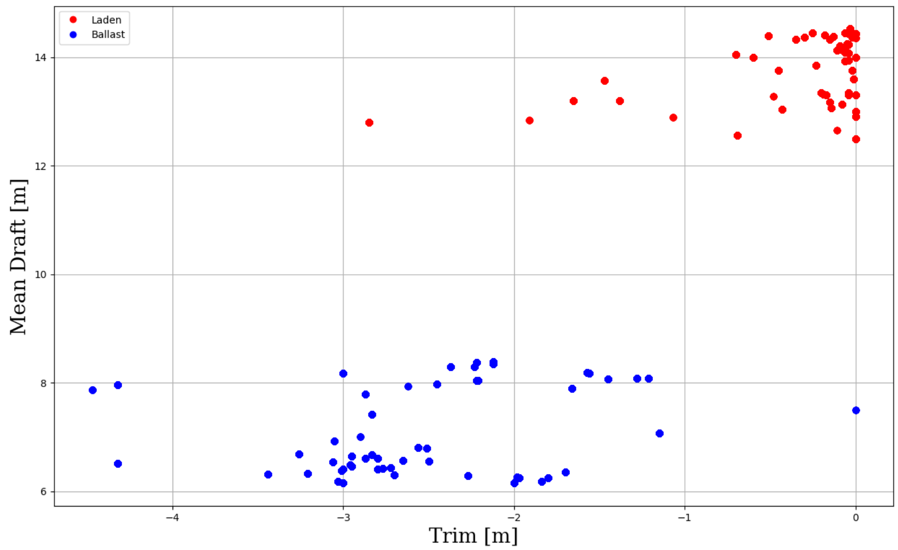

Figure 10: Mean draft vs trim diagram highlighting the different loading conditions.

Due to fouling accumulation, the vessel's hydrodynamic performance may differ drastically at different points in the operation timeline. Knowing the dates of the various maintenance events that took place during the reporting period is necessary to assess the changes in vessel performance over time. In Figure 11 the vessel operation timeline is shown, containing the date of each important event.

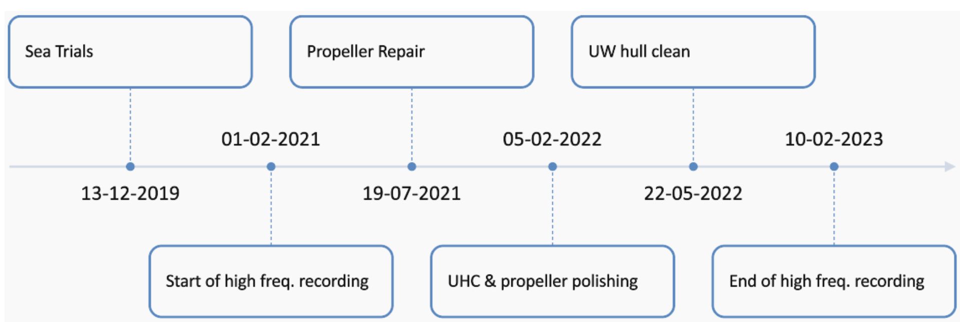

Figure 11: Timeline of the important events during vessel operation. UW: Underwater, UHC: Underwater hull cleaning.

Furthermore, an assessment of the vessel's hydrodynamic performance makes sense only in sailing conditions. Hence, it is important to identify the time intervals during which the ship was traveling. For this purpose, a list of the start and end dates-times of voyages during the reporting period is derived from noon reports, and then a dataset containing only voyages is extracted to exclude port calls. To ensure that the data analysis is focused on specific operational conditions, certain criteria are subsequently applied to the dataset, i.e., data points are rejected based on threshold values. A list of the lower and upper limits used in this study is provided in Table 5.

Table 5: Threshold values used for filtering per variable

Variable	Unit	Lower Limit	Upper Limit
SHP	kW	3000	-
STW	kn	6	-
Rate of turn	deg/min	-6	6
Current speed	kn	-3	2

To assess the impact of hull and propeller fouling on ship performance, the change over time of an appropriate KPI is observed. The KPI employed in this study is a customary propeller loading coefficient defined as follows:

$$KPI = \frac{P}{N^3} \tag{1}$$

where P is the ME power in kW and N is the propeller rate of revolution in rpm. In Figure 12 the KPI is plotted throughout the reporting period using separate colors for laden and ballast conditions to demonstrate that as the draft increases the KPI increases as well. The maintenance events dates are also shown in the plot, based on which the dataset is split into individual periods. Due to high variance caused by transients and various loading and weather conditions, the KPI is difficult to interpret directly; thus, a linear trendline is fit in each period, as defined between the maintenance events. The uptrend observed in each period's trendline accounts for the hull and propeller condition deterioration due to fouling. In addition, the drop in the trendline noticed after each maintenance event represents the improvement in vessel performance achieved because of the event.

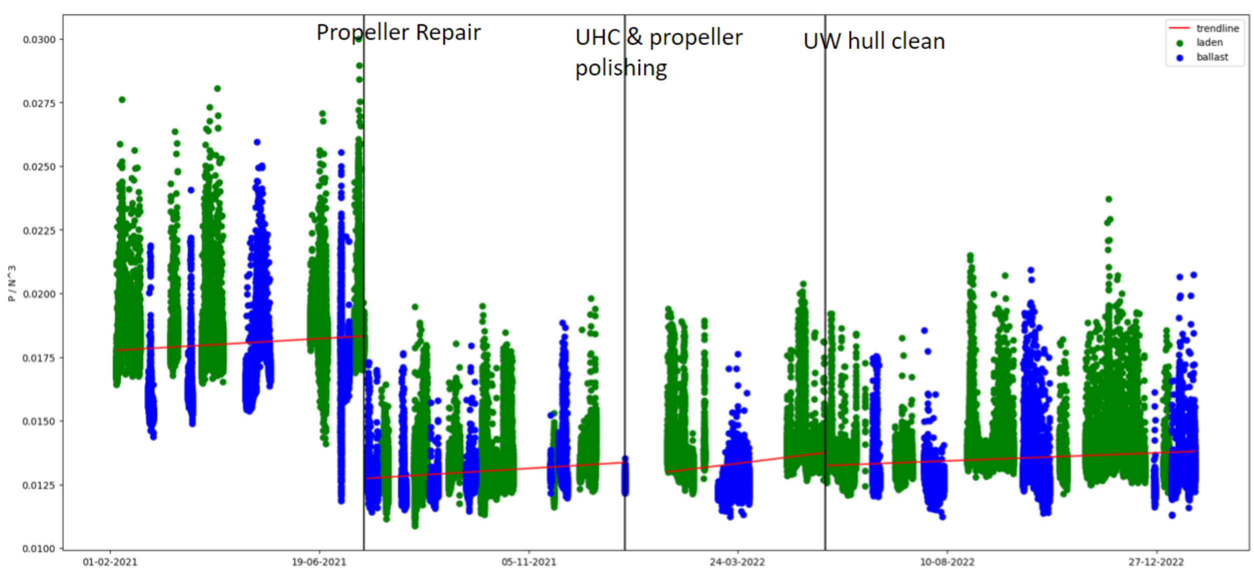

Figure 12: Monitoring of hull and propeller performance status and maintenance events.

Despite being intuitive and easy to implement, this approach presents certain shortcomings. First, it fails to answer the crucial question of how much power is saved with a maintenance event, and second, it does not account for the various factors affecting the ME power consumption. Power normalization methods for environmental factors exist (ISO, 2016), but they serve as a coarse approximation since they rely on assumptions that introduce uncertainty. For a more accurate and holistic approach to the problem, sophisticated data-driven methods ought to be employed. Using a well-tuned, highly accurate black-box model, the vessel's behavior in various conditions can be predicted. Such a model constitutes a digital twin of the vessel, meaning that it can be used to simulate scenarios (Nikolaidis & Themelis 2022).

The workflow of an ML process aimed at assessing ship performance and supporting maintenance optimization is shown in Figure 13. The main idea is to develop an ML model predicting ME SHP and train it on data corresponding to a few months after hull cleaning and propeller polishing. Then, this model can be used as a reference performance baseline representing the vessel's clean condition, to evaluate conditions with fouling (Laurie et al. 2021). The input variables that feed the model to predict ME SHP are termed features. The first step of the process regards feature engineering which consists of feature construction and feature selection. In feature construction, new variables are built using existing ones for a more accurate physical description of the problem, whereas in feature selection, the necessary input variables are determined with the help of appropriate statistical tools. The data preparation step deals with the elimination of erroneous data points, to derive a dataset free from anomalies that focuses on the desired operational conditions. Subsequently, various ML algorithms are evaluated, and different hyper-parameter combinations are explored, using state-of-the-art techniques, to develop a model with high predictive accuracy. Hull and propeller condition monitoring is achieved by employing the ML model to evaluate the expected ship performance.

Figure 13: Steps of an ML process for the development of a hull & propeller monitoring tool.

6. OPERATIONAL BASED HYDRODYNAMIC OPTIMIZATION STRATEGIES

As mentioned previously, the first part of the paper targets the identification of realistic operational conditions that will be used in the forthcoming hydrodynamic optimization studies. The aim is to examine whether any off-design conditions exist as well as to define the most appropriate space for key parameters such as speed and trim that would reflect their usual operational envelope. The relationship of this operational envelope with the ship's hull-form characteristics and appended devices creates a complex system. To be able to optimize such a system, the designer has to understand in depth its sensitivity and reactions to changes of the defining form parameters from a performance point of view. Knowledge of the system's behavior within the complete design space enclosed by constraints is needed, so that changes of the properties can be directly related to performance. Following previous research work we also utilize here driven systematic variation that yields real trend indications. The use of formal optimization has the advantage of producing actual shape variants. For retrofitting projects, the freedom for design decision is very limited. Typically, the forebody is modified to reduce wave resistance, while the aftbody shape is tuned for a low viscous resistance, high propulsive efficiency and homogeneous wake distribution. Therefore, two areas have been targeted among the partners of the project. The first one concerns the bulbous bow shape optimization, where each hull-form alternative will be evaluated in terms of calm water resistance and/or added resistance in waves at the specified loading conditions, speed and wave characteristics aiming at improving not only a specific operational point.

The optimization process utilized in this project will be carried out through the CAESES platform, while most of the computations will be delivered through CADENCE fine/Marine. The process starts with an appropriate parameterization of the geometry. Two options can be selected: partial and fully parametric model. Partially parametric modeling starts from an arbitrary geometry description, e.g., imported surfaces, offsets or meshes, and applies transformations that are defined by parameters. Fully parametric modeling in contrast starts from a set of parameters and generates the shape by stepwise setting up geometric entities that are connected to the parameters and to each other by dependencies. The most flexible and efficient approach in the case of retrofitting is usually that of a fully parametric model limited to the area of interest. After importing the initial geometry, the parts to be optimized are cut out or removed and finally replaced with a parametric geometry (Brenner et al. 2013). An efficient optimization strategy that has proved its validity in many commercial and research project consists of design space exploration with a systematic variation algorithm, followed by a local optimization with a deterministic search method. While the former gives a global overview of the design space, allowing for the identification of areas of interest, the latter will fine-tune the design to the optimal solution within that area.

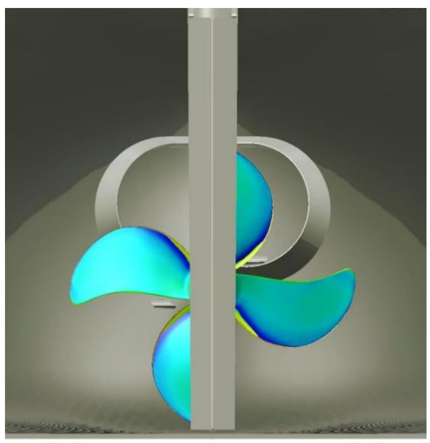

Figure 14: CFD Model with ESD

7. CONCLUSIONS AND NEXT STEPS

Following the analysis of the operational data and optimization strategies described above, a step further for the project will be to focus also on propeller retrofits. The aim will be to optimize the propulsion system for lower operating speed and lower thrust requirement due to installation of other energy saving technologies such as a wind-assisted ship propulsion system (WASP) or a hull air lubrication system (ALS). As it is part of RETROFIT55, WASP and ALS related partners will aid with providing their system specifications. Modifications of the original propeller will be considered by modified tip rake distributions to increase efficiency and by adjusting the blade roughness to control blade tip cavitation (e.g., Figure 14). Here it shall be noted that the presence of a WASP or ALS could require a possible expansion of the parameter space defined previously. Except from design measures, operational optimization related to the hydrodynamics such as trim optimization will be explored as candidates for the type of ships under examination.

Another operational measure as analyzed in the previous section is the proper cleaning and maintenance of the hull and propeller to prevent the development of biofouling. For this purpose, a condition-monitoring tool will be developed based on ML algorithms to predict the expected ship performance, evaluating and projecting the fouling potential in order to assist in decision-making.

8. ACKNOWLEDGMENTS

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