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Performance Indicators for Wind Powered Ships: Towards an Industry Standard

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Abstract

Wind propulsion has emerged as one out of many possible solutions to reduce GHG emissions from ships. The industry for wind propulsion solutions develops rapidly. This calls for some industry standardisation. A committee under ITTC is currently working on recommended procedures for performance indicators, performance prediction methods and sea trial procedures for wind powered ships. This paper proposes indicators that can enable fair comparison and facilitate the investment decision. A new sea trial procedures for wind propulsion solution verification is also proposed. Finally, the application of performance models in cost-saving split agreements, monitoring and weather routing of wind powered ships are discussed.

1. Introduction

Wind propulsion is one out of many technical solutions that can reduce the fuel consumption and improve the EEDI/EEXI of cargo vessels. By the end of 2022 there were 26 cargo vessels equipped with wind assistance technology. This number will be doubled the next year, *IWSA (2022)*, and the coming decades the number is predicted to increase to 10 000+ ships according to UK Clean Maritime, *Plan (2019)* and *Nelissen (2016).*

The number of companies providing wind propulsion technologies is increasing and includes both small start-ups, large established suppliers and recently also shipyards. The byers have in this first decade been dominated by front-runner ship owners willing to take risks and try the unknown. Recently, the ordinary shipping companies are joining as well. The wind propulsion community also includes designers, consultants, and suppliers of routing software. As the industry matures and grows, all these stakeholders need a common ground, standardised terminology and definitions especially regarding performance indicators and performance models.

The performance of conventional ships is usually expressed in terms of a speed-power curve. This is the basis for the communication around performance from the early concept phase, through design phase, yard contracts, sea trial verification, and charter party contracts. Once in operation, the performance monitoring and routing software use the speed-power curve in the baseline model. For wind powered ships the one-dimensional speed-power curve is not sufficient to describe the performance. The wind propulsor generates not only additional thrust but also a side force which causes significant drift and increased rudder angles. The thrust and the side force vary with the wind speed and the wind direction. This makes power modelling more complex, but the industry still needs simple transparent performance indicators, and methods for prediction and verification. Before this background, International Towing Tank Conference (ITTC) started up a Specialist Committee for Wind Assisted and Wind Powered Ships in 2019. This committee is, specifically tasked with developing key performance indicators (KPIs), guidelines for performance predictions and sea trial procedures for wind assisted ships.

2. Performance indicators and performance prediction methods

2.1. Current situation – a variety of indicators

Many new wind propulsion technologies (WPTs) exist on the market, ranging from rotor sails over kites and suction wings to rigid sails that resemble vertical aircraft wings. All these technologies have their specific strengths and weaknesses, which need to be assessed and quantified when selecting a WPT for a particular application. The wind propulsion community has, however, not yet agreed on common key performance indicators (KPI). Some technologies are described using aerodynamic coefficients, others by e.g. expected fuel savings. Percentage saving figures are commonly used, but it is often unclear what is included in the comparison. This complicates comparing technologies, puts the level playing field at risk, and delays investment decisions.

The following fictive test case is used to illustrate that ambiguous definitions of KPIs can be misleading. Three generic wind propulsion technologies (WPT 1, 2, and 3) are compared. The test case ship is a 5000-dwt general cargo / bulk carrier with a length of 90 m. The main parameters of the test cases are given in Table I.

Table I: The three test cases

	WPT 1	WPT 2	WPT 3
Ship	5000 dwt general cargo, L=90 m		
Max CL	9.6	5.8	1.3
Max CD	3.6	1.9	0.1
Active/passive	Active	Active	Passive
Projected area [m^2]	54	114	200
Deck footprint [m^2]	7	64	136
Foldable /tilting	no	yes	no

Four example routes are analysed (the first two routes are illustrated in Fig.1):

- Rotterdam-Bergen (return trip)
- Copenhagen-Riga (return trip)
- New York- English Channel (return trip)

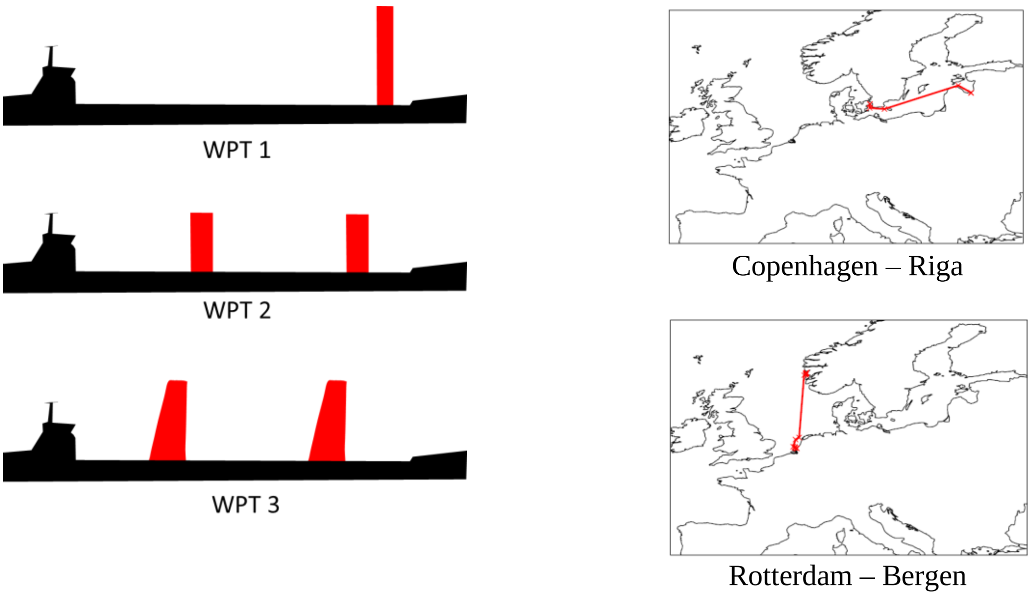


Fig.1: Generic Wind Propulsion Technologies fitted to a general cargo vessel

2.1.1 Aerodynamic characteristics as KPI

The first idea for a standard KPI could be to select an aerodynamic characteristic, such as coefficients of thrust force, side force, lift, drag at different wind angles. Fig.2 provides an illustration of some typical features. The test case WPT1 (dashed line) which has the highest lift coefficient has the highest max thrust (Cx). However, it has a narrower range of operation and a drag penalty in head wind since it is not tiltable. In order to rank the technologies, the probability distribution of wind angles that the ship will meet must be known. This depends on the specific route and the ship's speed. This illustrates that it may be misleading to describe the performance of a wind propulsion technology with a single aerodynamic characteristic.

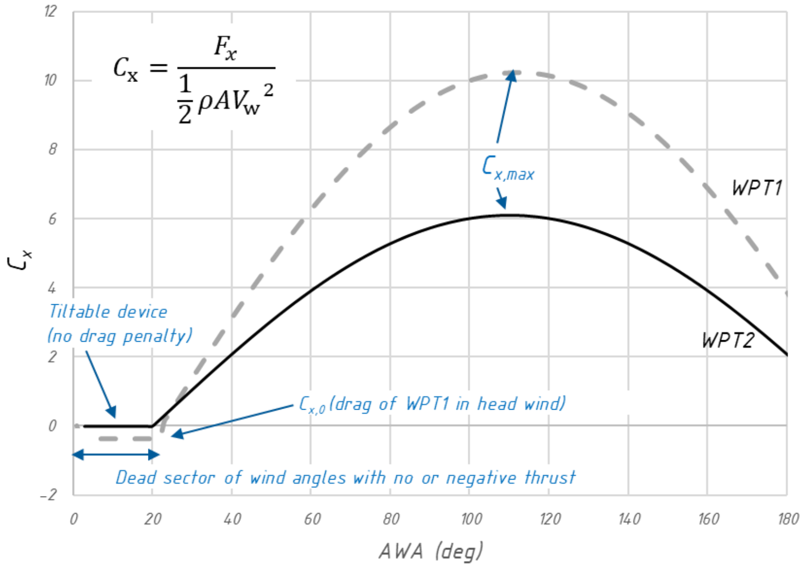


Fig.2: Example characteristics of WPTs, illustrated as thrust force coefficient (Cx) vs. apparent wind angle (AWA) curves for two different WPTs

2.1.2 Fuel saving as KPI

The benefits of wind propulsion technology are often described in terms a claimed percentage power or fuel saving:

$$\Delta P\% = \frac{P_{no\,WPT} - P_{with\,WPT}}{P_{no\,WPT}} \tag{1}$$

One could think that a percentage saving is a clear KPI that can be used for comparison between different installations, since it is nondimensional. Very often, percentage saving number are published without any further description of the specific cases. The following examples illustrate that this can be quite misleading.

The first and probably most common source of misunderstanding is to use the "up-to" performance indicator, meaning the saving at the most favourable wind condition. As shown in Fig.3, the power reduction of WPT 2 is 35% at the most favourable wind condition. Averaged over the various wind conditions on a given route, the power reduction on the best route is about a third of that, 12%. Communicating these two numbers would result in rather different expectations and business cases.

Another important issue with the percentage saving KPI is that it matters what the savings have been related to, i.e. what number is used in the denominator in Eq.(1). Fig.4 (left) shows the percentage power saving of the three test cases computed in different ways. First, the fuel saving is predicted for the sea legs in calm water. The ship's propulsion power when employing the WPT is compared to the propulsion power when there is no WPT, for the same sea leg and same speed.

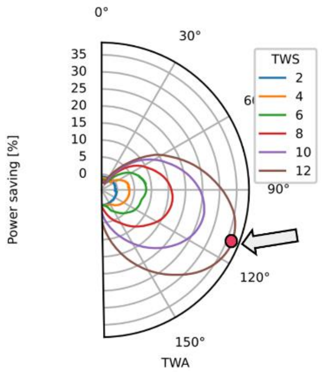
Secondly, the sea margin, or added resistance in waves, is included in the prediction. This is the standard procedures for some organisations, whereas others do not include it. It has minor effect on the predicted fuel or power saving in absolute terms (tons, kW), but it has a significant effect on the percentage, since it increases the denominator in Eq.(1). For WPT2, as an example, it makes the saving to decrease from 13% to 11.5%.

For the third group of numbers in Fig.4, the comparison is done against the ship's total fuel consumption, i.e. not only the fuel used for propulsion on the same sea legs. The denominator hence includes port manoeuvres, hotel load etc. That makes the saving to decrease further still, to 10% for WPT2. Note that the trends between the WPTs are preserved: in all cases WPT 2 is still the "winner".

Finally, the %-saving is also shown for a higher ship speed, 13 kn, to illustrate how much this can affect the saving number. The saving is now down to 7%. The trends are preserved in this case, however this is not always true since some technologies work better for higher speeds than others.

Fig.3 (right) shows that the power savings differ considerable between different routes. For WPT2, as an example, the fuel saving is 10% for the least favourable route and 16% for the most favourable. The trends between the three WPTs are preserved, although the advantage of WPT1 over WPT3 differs between the routes. These examples illustrates that a percentage saving number, taken out if its context, may be misleading. A percentage number gives the false impression that it can be universally compared with other percentage saving predictions.

In addition to the possible sources of confusion explained here, the methods for deriving the numbers differs completely between different organisations and can be based on everything from experimental test, CFD to experienced based guesses. Without a common definition of performance indicators and methods to derive them, it is very difficult to compare performance expectations and claims. That is the reason for the deriving the proposed guidelines described in the next section.



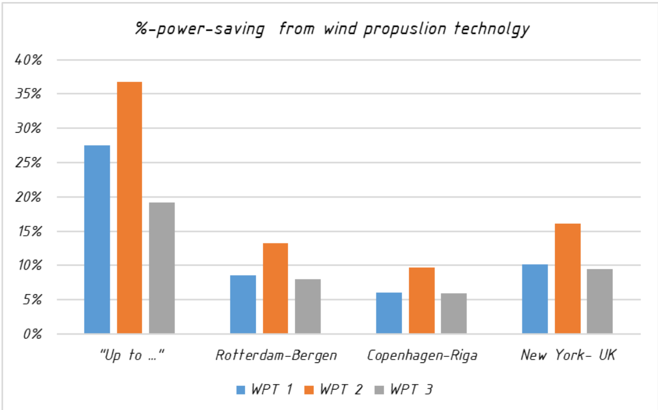


Fig.3: Sometimes the performance is expressed as "up to xx%", meaning the performance at the most favourable wind condition. The averaged wind condition on a route gives quite different saving.

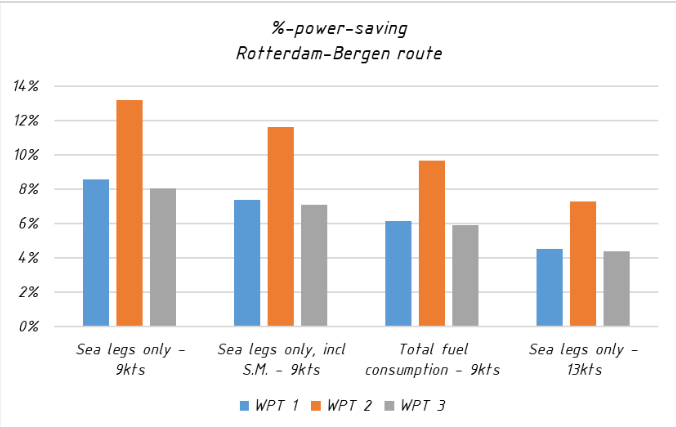


Fig.4: Percentage power saving can be computed in different ways, and for different conditions, which results in different performance expectations

2.1. Proposed guidelines for performance predictions of wind assisted ships

The Specialist Committee for Wind Assisted and Wind Powered Ships under the 30th ITTC is currently preparing guidelines for prediction of power saving of wind propulsion technology. This section gives an outline of how the guidelines will be structured and how they connect to performance indicators. In the process to derive common KPI's, several focus group meetings were held with industry stakeholder in cooperation with the International Wind Ship Association (IWSA) and the Interreg North Sea region project WASP. The proposed guidelines have also been discussed with the French WindShip association and it has been presented at the RINA conference Wind Propulsion for Ships in London 2023, *Werner (2023).*

Note that the guideline below is a draft proposal. By presenting it here, the ITTC Specialist Committee hope to receive input and comments from the industry before publishing the final ITTC guidelines.

The proposed guideline is the first attempt to create a common ground and common terminology for expressing performance expectations of wind powered ships at design stage. They focus on methodologies for predicting the power saving of a wind powered ship on a route at design stage, compared to the corresponding ship without wind propulsion. The guidelines give an overview of the type of methods that are suitable for the different stages of the ship design process, considering the balance of confidence level and computational cost. It is not the intention to provide detailed procedures. It is assumed that the organization conducting the predictions has relevant background knowledge and tools.

The guidelines are intended to be used by organizations conducting performance predictions for wind powered ships (e.g. consultants, yards, technology providers). They are also intended to be used indirectly by all stakeholders who need to discuss the resulting performance indicators (e.g. ship owners, operators, investors). By providing standard indicators that are linked to prediction procedures of varying confidence levels, the guidelines aim to provide a common terminology for all stakeholders.

The guidelines are mainly applicable to cargo vessels with wind assistance technology (moderate size of wind propulsion), although they can to some extent be applied to vessels with primary wind propulsion. Sailing yachts, racing boats or traditional sailing vessels are not in the scope.

The focus of the guidelines is the <u>relative performance</u> of wind assisted ships, i.e. the power saving <u>relative</u> to the same ship with conventional motor propulsion. The industry today still sees the conventional motorship as the benchmark which the business case for novel technologies relate to. However, this perspective may change in future versions. It is expected that the guidelines will be updated frequently the coming years as the knowledge and tools in the industry develops.

Deriving the expected fuel saving from a wind propulsion solution involves four principal steps:

1. Generating background data. (Towing tank tests, wind tunnel experiments, CFD simulations).
2. Generating models from the background data, which describes the sub-systems response to a changed of state. For example, describing the aerodynamic force of a sails in different wind angles.
3. Deriving steady state force equilibrium with Velocity Prediction Programs (VPPs) or Performance Pre-diction Programs (PPPs).
4. Route studies, where the variation of environmental conditions that the vessel will meet on a route is combined with the static performance model to derive the expected average power or energy saving due to the wind propulsion.

Predictions of the power savings from wind propulsion systems are used at various stages of the design process, from initial assessments to final performance expectation. The guidelines are arranged into various levels of accuracy to meet the specific needs, requirements, and availability of data of each stage. The fidelity and the required efforts increase with increasing level. An overview is given in Table II, the complete table is given in Appendix.

Table II: Overview of methods for prediction of power saving of wind propulsion technologies

	Level 0	Level I	Level II	Level III	Level IV
Applicability ->	**WPS rated power**	**Early idea**	**Early business case assessment**	**Business case & Performance expectation**	**Advanced Business case & Performance expectation**
Force balance	1DOF	1DOF	3-4DOF	4DOF	4 DOF (at least)
Aerodynamics	Specific	Generic	Low/Mid fidelity*)	High fidelity*)	High fidelity
Hydrodynamics		Generic	Low/Mid fidelity	High fidelity	High fidelity
Machinery interaction			Generic SFOC + limitations	Specific SFOC + limitations	Specific SFOC + limitations
Weather on the route		EEDI or intended route	Intended route	Intended route	Intended route or weather routing
					Optional effects: e.g. ship motions and varying wind energy management optimisation

*) Low/Mid fidelity methods can be for example high fidelity data or regression models from similar cases, or case specific lifting line methods
**) High fidelity refers to case specific CFD, model test or full-scale test.

2.2.1 Level 0 Wind Propulsion Unit rated power

In the first phase, when scanning the market and shortlisting possible devices, it would be convenient to have an indicator of the available power of a single, stand-alone wind propulsion unit, independent of the ship and route. For this purpose, a WPU rated power indicator is proposed:

$$PSP0_{[kn]} = \sum_{i,j}^{n,m} \left[\frac{F_x \cdot V_s}{\eta_D} - P_{WPU-in}\right]_{i,j} \text{ x } \left[\mathrm{W}_{i,j}\right] \tag{2}$$

Where $\mathrm{W}_{i,j}$ is the EEDI weather matrix (MEPC.1/Circ.815 (2013))
η_D=0.7
$F_{x,wpu}$ is the thrust force from the WPU at the corresponding winds as the weather matrix (N)
V_s is the ship speed (m/s)
P_{WPU-in} is the power consumption of the WPU (W)
kn is the V_s in knots

PSP stands for power saving potential, and 0 indicates the Level. The PSP-0 can be derived at a range of standard ship speeds, for example 10, 15, 20 knots.

The thrust forces $F_{x,wpu}$ should be determined by the provider with the best possible available methods. Industry standard is today RANS CFD and/or wind tunnel test. Predicting the max lift of wing sails with RANS CFD is not trivial. The choice of turbulence model and grid may change the stall point considerably and result in overpredicted performance. Flettner rotors are seemingly easy geometries but exhibit complex dynamic flow structures and require unsteady computations with carefully selected CFD parameters. Wind tunnel test on the other hand suffer from scale effects, which are as today not fully qualified for the type of large structures in focus here. In summary, a combination of unsteady RANS in full scale and model scale, and wind tunnel test is today the recommended source of data for the WPU rated power. This may change, as the technology develops.

2.2.2 Level 1 Early idea

Level I provides a simple approach for obtaining an early estimate of the potential of wind propulsion technology. Compared to Level 0, the prediction is done for a given ship. It gives an indication of power saving but is not intended to be used for business case decision support. Several physical effects are neglected such as side force and yaw moment, propeller underload, and aerodynamic interaction between hull and wind propulsion units. This which will in general give a non-conservative prediction.

The thrust force from the wind propulsion units can be based on generic data, open published data or data from similar cases, if no case specific data is available. The wind distribution on a route is taken into account by a general wind probability matrix, for example the EEDI weather matrix, *IMO (2013)*, which represents all major world-wide shipping routes.

2.2.3 Level II Early business case assessment

Level II predictions is intended for input to the early business case. At this level of predictions, the intention is to get more reliable estimates of the power saving potential, at a level of effort that still allows for assessing several different options. Most of the important physical effects are accounted for, however with low/medium fidelity methods. The guidelines give example of suitable methods for modelling the various physical effects.

A route study is required to properly accounting for the wind distribution. This is done with a statistics route simulation for example of Monte Carlo type or a voyage simulation with fixed speed. The result of the route study is the average power requirement $\overline{P_{wps}}$ and $\overline{P_{no\ wps}}$ for the ship with and without wind propulsion system respectively, for the same ship's speed and same route.

2.2.4 Level III Business case & Performance expectation

Level III is intended to be final level for most wind-assist applications. This level of predictions is intended for evaluating power saving potential to a degree at which performance contracts can be established between supplier and buyer. As such, it sets requirements to the use of high-fidelity methods for the various modelling approaches, and covers all physical effects that at the time of writing is considered to have noticeable influence on the power saving potential. High-fidelity methods are typically 3D URANS (validated with experiments), or model test. The route study is carried out in the same manner as for Level II.

2.2.4 Level IV Advanced Business case & Performance expectation

Level IV is recommended for ships that use extensive weather routing, primary wind powered ships, and ships with advanced hybrid propulsion systems. The main difference from Level III is that the route studies can include weather routing and speed optimisation. Hence, the route and speed may be different for the case with and without wind propulsion. Level IV performance modelling requires methods that are yet on the research forefront, for example aero-hydrodynamic interaction in a sea way.

2.2 Performance Indicator for Level I-IV

The guidelines recommend three performance indicators according to Table III.

Table III: Recommended KPI's

		Level 0	Level I	Level II	Level III	Level IV
Preferred	Rated power (kW)	PSP-0				
	Power Saving Potential (kW)		PSP-I	PSP-II	PSP-III	
	Energy Saving Potential *(MWh)*					ESP-IV
Optional	Percentage Saving Potential – Propulsion power (%)			PSPp-II	PSPp-III	PSPp-IV
	Percentage Saving Potential – Total fuel (%)			PSPt-II	PSPt-III	PSPt-IV

Power saving potential PSP for Level I – III is derived as

$$PSP = \overline{P_{no\ wps}} - \overline{P_{wps}} \tag{3}$$

where $\overline{P_0}$ is the yearly average power on a given route for the ship without wind propulsion system
$\overline{P_{wps}}$ is the yearly average power on a given route for the same ship with wind propulsion system, for the same ship speed.

The word "potential" indicates that the result is the technical potential that the installation can deliver. During operation, many practical aspects may include the real saving, such as maintenance, damage, operating in confined waters. The saving may also be larger than predicted, if the ship is routed with respect to the wind in a favourable way.

As discussed in the previous section, when it comes to the percentage saving indicators it matters what to include in the denominator. The *PSPSp* indicator includes the propulsion power only, and the route includes the sea leges only (pilotage to pilotage).

$$PSPp = \left(\overline{P_{no\ wps}} - \overline{P_{wps}}\right)/\overline{P_{no\ wps}} \tag{4}$$

The *PSPt* indicator relates the fuel saving to the ships total fuel consumption including auxiliary power, harbour manoeuvres etc:

$$PSPt = \left(\overline{FOC_{no\ wps}} - \overline{FOC_{wps}}\right)/\overline{FOC_{no\ wps}} \tag{5}$$

For Level IV prediction, it is feasible to derive the energy saving rather than average power saving. The comparison can even be against other ship sizes and ship speeds. The indicator is denoted Energy Saving Potential (*ESP*), which is derived by comparing the average energy consumption to transport the same transport work between the same ports.

3. Sea trial procedures

After the installation of a wind assisted solution, there is a need to verify the performance in real life. Since wind propulsion for modern, commercial ships is still a novelty, the community has not converged towards a standard procedure for conducting full scale verification tests. A practical sea trial methodology was proposed and tested in the EU Interreg North Sea Region project WASP, *Werner (2022)*. The same approach with minor modifications is now proposed for the ITTC Recommended Procedures. A short description is given here.

Like a conventional sea trial, the WASP sea trial consists of a series of short runs. The main difference to a conventional sea trial is that the outcome is not the absolute value of the speed-power curve, but the power reduction due to the wind propulsion system. The effect of the wind propulsion system is extracted by comparing speed and power of single runs with and without rotor for the same wind condition. This is repeated for 5-6 wind directions. The measured speed difference is converted to a power difference using the shape of the speed power curve and with some corrections for speed differences.

In contrast to the normal procedures, the current correction based on double runs cannot be applied when wind propulsion is active. To overcome this, the speed is measured using the ship's log. Since the purpose is to derive a speed difference, the poor uncertainty of the speed logs is acceptable.

The WASP sea trial can be carried out at any wind conditions that gives sufficient driving force from the wind propulsion system, typically between Bf 4-7. It requires no additional instrument than what is used on a normal sea trial: speed, shaft power, anemometer. However, it is acknowledged that the largest error source for the WASP sea trial is the disturbance of the hull on the wind measurement. This can be overcome by using a Lidar, either during the trial or by establishing correction tables of the anemometer based on earlier Lidar measurements in various wind conditions. This is, however, a costly approach and can therefore not be requested in general.

Fig.5 shows example of sea trial results for three of the ships tested in the WASP project, *Werner (2022).* The minimum WASP sea trial program covers only 5-6 wind directions and one wind speed. It can therefore only provide a spot check of the complete performance matrix (the polars). This is however in analogy with the conventional sea trial, which only verifies a few speeds at calm water and one draft, whereas the real operation includes a wider range of conditions.

The wind propulsion industry is still in an early phase, and many knowledge gaps remains to be filled. This includes the performance prediction, where effects such as hull-WPU interaction and dynamic effects are yet hard to quantify. Another knowledge gap is the uncertainty of WASP sea trials, since only less than 10 has been conducted so far. Therefore, we recommend to <u>not yet</u> use WASP sea trials to strictly confirm performance guarantees in a contractual context. However, it is strongly recommended to request at the minimum a WASP sea trial program to confirm the performance expectation. Not only will that give important information for the provider and ship owners for future investments. It is also important knowledge that can be used in the operation, as will be discussed in the following sections.

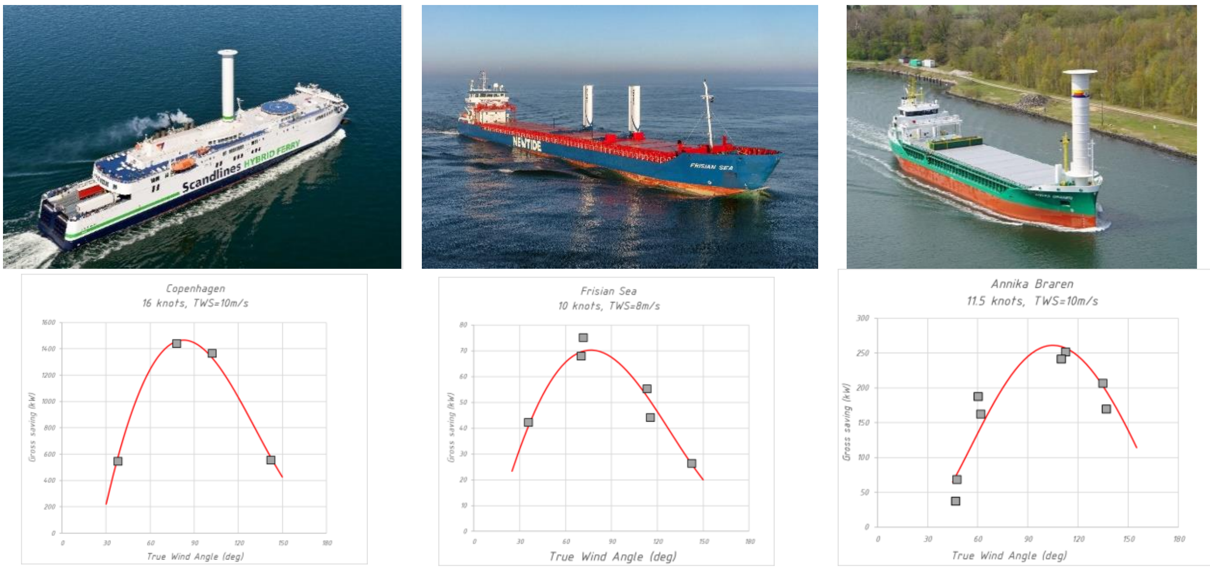


Fig.5: Example of WASP sea trial results

4. Cost-saving split – a proposed approach

Note that Section 4 and 5 are outside of the scope of ITTC and represent our suggestions only.

The investment cost for retrofitting vessels with wind propulsion technology may be a hinder, especially for the chartered fleet. To lower this obstacle, owners and charterers can agree to share the cost and the resulting fuel savings. There are also examples in the industry of providers offering pay-as-you-save contracts. These types of arrangements require a procedure for estimating the actual saving. Due to the complex physics and dependency on wind variation, this is not trivial to derive. To measure the forces produced by the wind propulsion devices seems like an obvious solution, but that kind of measurements is still, to our knowledge, not yet a matured technology for use in commercial shipping. To rely on advanced force measurements could be unreliable, expensive and inaccurate.

We propose here instead a robust solution in three steps:

1. The fuel saving is predicted as described in chapter 2 using agreed confidence level. This results in a matrix (or polar diagram) of power saving for combinations of wind speeds and wind directions, speeds and drafts.
2. The power saving matrix is confirmed by a WASP sea trial (spot check) and possibly updated if not confirmed. All parties agree on the power saving matrix.
3. During operation, the wind conditions that the ship experience are obtained from AIS and metocean data, alternatively measured wind by the ship's anemometer if it is logged. Statistics of the experience weather over a given period is easily combined with the agreed power saving matrix to give an acceptable estimate of the power saving. Of course, excluding days when the wind propulsion device is down due to maintenance or repair.

The advantage of this approach is that it is transparent, understandable by all parties (hence minimising risk for claims and disputes), technically sound, robust, and cost-effective. It does not rely on expensive or fragile sensor systems and is thus fail safe.

5. Models for weather routing and performance monitoring software

Performance monitoring and weather routing are today well-established fuel saving measures. For wind powered ships, weather routing has in theory even higher saving potential. Software for weather routing and performance monitoring require baseline performance models of the actual ship. They usually consist of speed-power curves at various drafts derived either with CFD or model test. Routing software for wind powered ships does however require more complex baseline models that reflect the aerodynamic and hydrodynamic force balance in 4 degrees of freedom, including drift and rudder angles etc. The aerodynamic part needs to include the control system algorithm of the wind propulsion system. Since the route optimiser is likely to lead the ship to a windy area, where there are also more waves, it is important that the performance model can accurately predict the wave added resistance including the aero-hydro coupling. This means a Level 4 performance model. The baseline models for monitoring software do not need to be that complex but at least a Level II model is probably needed.

Incorrect performance models risk to deteriorate the potential of performance monitoring as well as the route optimisation software. Therefore, to verify or correct the performance model with a WASP sea trial is very valuable.

6. Conclusions

Wind propulsion technology for modern cargo vessels has developed from non-existing to a viable industry in a few years and it is expected to expand further before the decade is out. This calls for technical development in a range of aeras. In this paper a number of issues regarding performance prediction procedures and performance indicators are discussed:

- No standard performance indicator or performance perdition methods exist. A specialist committee under ITTC is currently preparing the first guidelines, as an attempt to create a common terminology for expressing performance of wind powered ships at design stage.
- Verifying the performance of wind propulsion installations in full scale is highly recommended, especially now in the developing phase of this new industry. A procedure for conducting

and analysing sea trials for wind propulsion system verification is proposed and will be published by ITTC.

- Cost-saving split or pay-as-you-save contracts can be a way to overcome the investment burden for ship owners. A feasible strategy for deriving the saving in the daily operation is proposed.
- Weather routing and performance monitoring software for wind powered ships will require more complex baseline models.

We welcome readers who have comments or suggestions to the proposed methods to contact us and continue the discussion.

Acknowledgement

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Appendix

Overview of methods for prediction g power saving of wind propulsion technologies

		Level 0	Level I	Level II	Level III	Level IV
	Applicability ->	***WPS rated power***	***Early idea***	***Early business case assessment***	***Business case & Performance expectation***	***Advanced Business case & Performance expectation***
	Performance Indicator	*PSP-0*	*PSP-I*	*PSP-II*	*PSP-III*	*ESP-IV*
Force balance	Degree of freedom	*1DOF*	*1DOF*	*3-4DOF*	*4DOF*	*4 DOF (at least)*
Aerodynamic	WPU thrust	*Specific*	*Generic*	*Low/Mid fidelity**)	*High fidelity**)	*High fidelity*
	WPU power consumption	*Specific*	*Generic*	*Specific*	*Specific*	*Specific*
	WPU-WPU interaction			*Low/Mid fidelity*	*High fidelity*	*High fidelity*
	WPU-superstructure interaction			*Low/Mid fidelity*	*High fidelity*	*High fidelity*
Hydrodynamic	Ship resistance		*Generic*	*Specific*	*Specific*	*Specific*
	Ship added resistance in waves		*Generic*	*generic*	*Specific*	*Specific*
	Propeller efficiency		*fixed* h_D	*Specific or adapted propeller series*	*Specific*	*Specific*
	Propulsive coefficients		*fixed* h_D	h_0 *varies with propeller load. Fixed* h_H, h_R	*Include also effect of leeway on propeller*	*Include also effect of leeway on propeller*
	Hydrodynamic effect of side force			*Low/Mid fidelity*	*High fidelity*	*High fidelity*
Engine	Machinery interaction			*Generic SFOC + limitations*	*Specific SFOC + limitations*	*Specific SFOC + limitations*
Voyage	Weather modelling		*EEDI or intended route*	*Intended route*	*Intended route*	*Intended route or weather routing*
Constraints	Operational constraints and limitations			*Limiting wind speed from provider Reasonable rudder and heel*	*Specific limits on loads, rudder, heel, engine.*	

Mix	Effects of ship motions and varying wind, incl control systems response time					*optional*
Mix	Hybrid-propulsion (diesel electric) with energy management optimisation					*optional*

Simplified and Accurate Models of Correction for Wind and Waves on Onboard Monitoring Data
- Effects on Evaluation of Ship Performance in Calm Seas

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Abstract

The OCTARVIA project phase 2 developed a simplified method for estimating propeller open-water characteristics, self-propulsion factors, hull form data, and superstructure parameters for ship performance evaluation using monitoring data. In the project, the evaluation based on the simplified method is called "Level-1 evaluation" and that based on model tests and the real form parameters is called "Level-2 evaluation". This paper compares Level-1 and Level-2 evaluations on ship performance in calm seas for 14 ships in operation including domestic and ocean-going ships. The comparison clarifies the effectiveness of Level-1 evaluation as results equivalent to Level-2 evaluation.

1. Introduction

Ship performance monitoring is globally recognized as a means for measuring performance of ships in operation and the data collected through ship performance monitoring should be analysed in appropriate way to evaluate the ship performance with accuracy. The OCTARVIA project where 25 stakeholders in Japan Maritime Cluster participated discussed and established the method for collecting and analysing the data and evaluating the ship performance. The method is featured by Resistance Criteria Method (RCM) in which filtering of the data is conducted based on resistance increase rate from a specified sea condition such as calm sea condition. The subsequent project "OCTARVIA Project phase 2" launched in March 2022 progresses the applications of the established method to ships in operation to clarify the effectiveness of the method.

The one of purposes of the monitoring is to evaluate ship performance in calm seas. To achieve this purpose, the established method includes a correction for wind and waves on engine revolution and output prior to conducting RCM. The correction requires not only propeller open characteristics and self-propulsion factors obtained by model tests but also form parameters expressing hull shape below waterline and superstructure which are provided for predicting response functions of added resistance due to wind and waves. While shipbuilding companies are accessible to these data, it is not easy for the other parties in maritime cluster to use such data. Bearing in mind that various parties in the maritime cluster use the monitoring data, the simplified method for estimating propeller open characteristics, self-propulsion factors, hull form data, and superstructure parameters is developed. In the project, the evaluation based on the simplified method is called "Level-1 model" and that based on model tests and the real form parameters is called "Level-2 model".

This paper presents the comparisons between Level-1 and Level-2 models on ship performance in calm seas for 14 ships in operation including domestic and ocean-going ships. The comparison clarifies the effectiveness of Level-1 model as equivalent to Level-2 model.

2. Simplified and Accurate Models

Onboard monitoring is conducted mainly by shipowners who operated ships. The data collected from onboard monitoring (called "onboard monitoring data") is not only in the hands of the shipowner, but also in the hands of shipyards and marine equipment manufacturers. In other words, now that onboard monitoring is widely used, any interested party in the shipping industry can obtain onboard monitoring data, which enables them conduct analyses of onboard monitoring data and evaluate ship performance based on the analyses.

The evaluation method of ship performance in calm seas based on onboard monitoring data established by the OCTARVIA project includes corrections on engine revolution and power for wind and waves. Since the correction is conducted in compliance with *ISO15016(2015)*, it is necessary to prepare the following parameters:

- added resistance in waves based on hull form data,
- added resistance in wind based on superstructure parameters,
- propeller open characteristics (POC), and
- self-propulsion factors.

To ensure the reliability of the corrected engine revolution and power, these parameters should be estimated with accuracy. For parties other than shipyards obtaining these parameters is a hurdle. For surmounting the hurdle, the OCTARVIA project discussed "Level-1 evaluation (Level-1)" as the simplified evaluation. Level-1 estimates the four parameters based on ship principal particulars.

On the other hand, it is not difficult for shipyards to prepare these parameters since they have hull form data and general arrangement that allow them to estimate added resistance in waves and that in wind. *Ishiguro et al. (2016)* and *Orihara et al. (2019)* estimated sea margin based on the analysis of onboard monitoring data. In their studies, they used their own hull form data to estimate added resistance in wind and that in waves. Further, although not explicitly stated, POC and self-propulsion factors obtained by model test or numerical simulations seemed to be used. The OCTARVIA project named the evaluation above "Level-2 model (Level-2)".

The parameters in Level-1should have equivalent accuracy with those in level-2. For this purpose, *Sogihara et al. (2019)* conducted the validation of the parameters in Level-1. A comparison of added resistance in regular waves and POC for the DTC containership is shown in Fig.1 and Fig.2, respectively, as the validation.

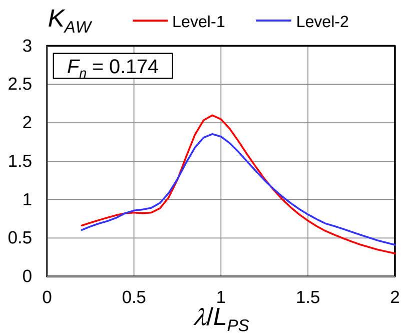

Fig.1: Added resistance in regular waves

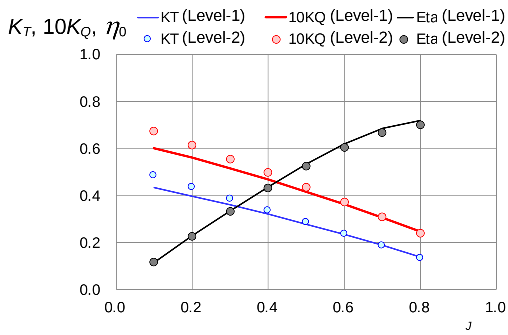

Fig.2: Propeller open characteristics

In Fig.1, red line and blue line indicates the estimated added resistance by Level-1 and Level-2, respectively. In Fig.2, solid line and plots indicates the POC estimated by Level-1 and model test data provided for Level-2, respectively. These figures show that Level-1 has equivalent accuracy with Level-2 for the estimation. The definition of Level-1 and Level-2 is summarized in Table I.

Table I: Definition of Level-1 and Level-2

Item	Simplified model (Level-1)	Accurate model (Level-2)
Hull form data and parameters	Estimated based on ship principal particulars (Using EAGLE-OCT.-web, *Sogihara et al. (2022)*)	Lines Data
Superstructure parameters		General Arrangement
Propeller open characteristics		Model tests, Numerical simulations
Self-propulsion factors		

3. A Model of Ship Performance established by OCTARVIA Project

Sogihara et al. (2020) presented the evaluation model of ship performance using onboard monitoring data which had been established by the OCTARVIA project. The flowchart of the evaluation model is illustrated in Fig.3.

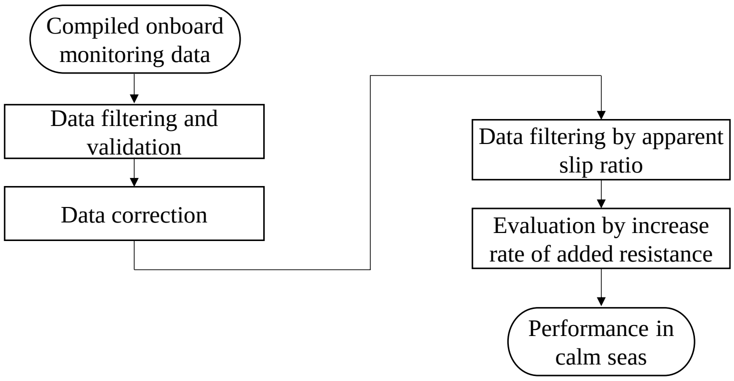

Fig.3: Flowchart of the evaluation model established by the OCTARVIA project.

3.1 Compiled onboard monitoring data

The evaluation model developed by the OCTARVIA project (hereafter “OCTARVIA model”) requires onboard monitoring systems to collect the following items.

- ship speed over ground
- ship speed through water
- heading angle
- ship course
- rudder angle
- wind speed and direction
- wave dimensions (significant wave height, mean period, primary direction)
- engine revolution
- engine power
- ship draft and displacement

Items indicated above other than wave dimensions and draft at port can be collected as time history, therefore the mean value for a certain period should be calculated onboard for each item. The wave dimensions, which are necessary for evaluating ship performance based on onboard monitoring data, are obtained by either hindcast or observation by measurement instruments such as wave radar. The OCTARVIA project uses the hindcast data provided by Japan Weather Association, *Sato and Matsuura (2019)*.

Ship draft in port is usually recorded to logbook and the recorded draft can be used in the OCTARVIA model. Ship displacement can be calculated based on hydrostatic table. In using the draft measured by draft gauges equipped to the ship, attentions should be paid because it can be affected by ship static trim in voyages. Each item should be compiled into tabular format.

3.2 Data filtering and validation

The OCTARVIA model does not use the data collected in unsteady conditions such as ship’s acceleration or rudder operation. In ship’s acceleration, ship speed continues to increase, which cannot be considered as steady condition. Similarly, ship’s course changes continuously under rudder operation, which is treated as unsteady condition.

It is well known that ship speed through water cannot be measured with accuracy. The OCTARVIA model focuses on the difference between speed over ground and that through water. The data with the larger speed difference are eliminated from the complied onboard monitoring data.

To extract the data in steady condition and with the small speed difference, the criteria shown in Table II is applied in the OCTARVIA model.

Table II: Criteria for data validation

Item	Criteria	Purpose
Engine revolution [rpm]	more than 40% N_{EMCR}	Eliminate the unsteady data measured under the acceleration after departure and the deceleration before arrival
Drift angle [deg.]	less than 3.0*	Eliminate the data under rudder operation
Rudder angle [deg.]	less than 5.0*	
Difference between ship speed over ground and through water [knot]	less than 0.5*	Eliminate the data affected by the current Ensure the accuracy of speed through water

* denotes an absolute value.

3.3 Data correction

The evaluation of ship performance in calm seas requires the data collected to those in calm seas. The OCTARVIA model applies Extended Power Method (EPM, *STRASSER et al, (2015)*) to the corrections of engine revolution and power for wind and waves.

Prior to the correction, the data within 5% range of the representative displacement is extracted. For the extracted data, ship speed through water is corrected to the speed at the representative displacement according to Eq.(1).

$$V_{rep} = V_{voy}\left(\frac{\Delta_{voy}}{\Delta_{rep}}\right)^{\frac{2}{9}} \tag{1}$$

V is the ship speed through water and Δ the displacement. Subscripts '*voy*' and '*rep*' denote the value in voyage and representative displacement, respectively. The representative displacement can be determined arbitrarily and for example provided with the design full condition.

Flowchart of correction of engine revolution and power for wind and waves is show in Fig.4. Added resistance in wind is calculated by the method based on the regression formula in which the added resistance coefficient is expressed by superstructure parameters such as lateral projected area above waterline, *Fujiwara et al. (2006)*. Added resistance in waves is calculated by the theoretical method with simplified tank tests in short waves or empirical formula which can estimate the added resistance in any wave direction, *Tsujimoto et al. (2015).* The methods for calculating added resistance in wind and waves were discussed and validated by ITTC specialist committee and consequently concluded to be most accurate, *ITTC (2014).*

Using the measured ship speed through water, engine revolution and power, the propeller working point in actual seas can be calculated. In conjunction with propeller open characteristics and self-propulsion factors, total resistance in actual seas can be calculated. Subtracting the added resistance ΔR from the calculated total resistance R_{ms} gives ship resistance in calm seas R_{id} as shown in Eq. (2).

$$R_{id} = R_{ms} - \Delta R \tag{2}$$

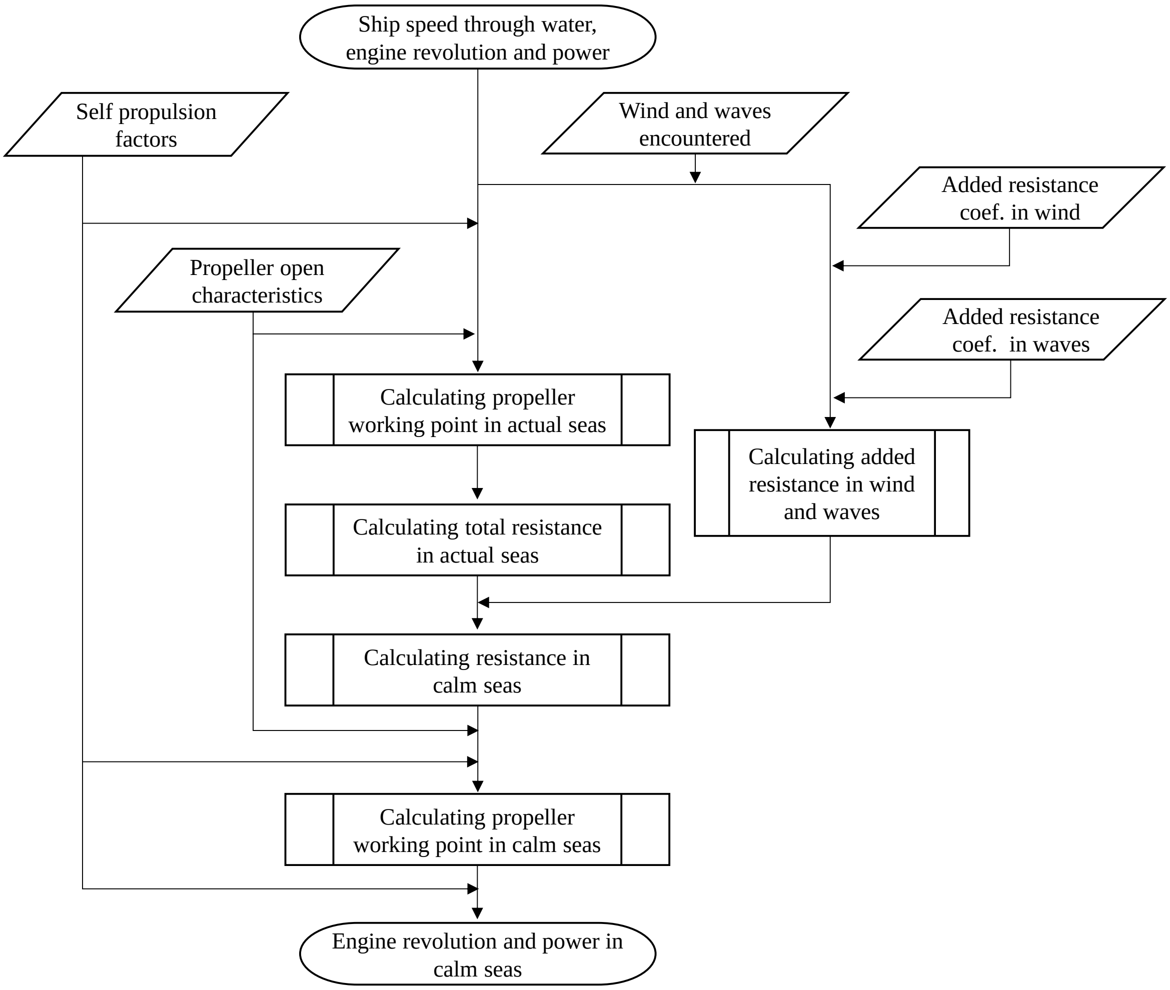

Fig.4: Flowchart of correction of engine revolution and power

Based on the propeller open characteristics and self-propulsion factors and the obtained resistance in calm seas, the propeller working point in calm seas can be calculated and the engine revolution and power in calm seas is obtained.

3.4 Data filtering by apparent slip ratio

The corrected data which is provided for evaluating ship performance in calm seas often scatter due to lack of accuracy of collected data. For the accurate evaluation of the ship performance, the collected data should not scatter and the data set with low scattering should be prepared. In this regard, the OCTARVIA model introduced the filtering by apparent slip ratio. It is reported that applying the filtering by apparent slip ratio can reduce the extent of data scattering, *Sogihara et al. (2020)*.

3.5 Evaluation by increase rate of added resistance

Conventional methods set criteria on ambient conditions such as wind speed to extract the data which can be deemed to be in calm seas. For example, *ISO19013 (2016)* suggests that the data in calm seas should be those in less Beaufort 4. The OCTARVIA model introduces increase rate of added resistance δR in order to consider that the extent of ambient conditions depends on ship size. The increase rate is defined by Eq. (3).

$$\delta R = \frac{\Delta R}{R_{id}} \tag{3}$$

The detail of the evaluation method using δR is described in *Sogihara et al. (2020)* and here briefly explained. The evaluation method, which is called "Resistance Criteria Method (RCM)", contains the process of 'two-way' evaluation involving δR. The outline of RCM is shown in Fig.5.

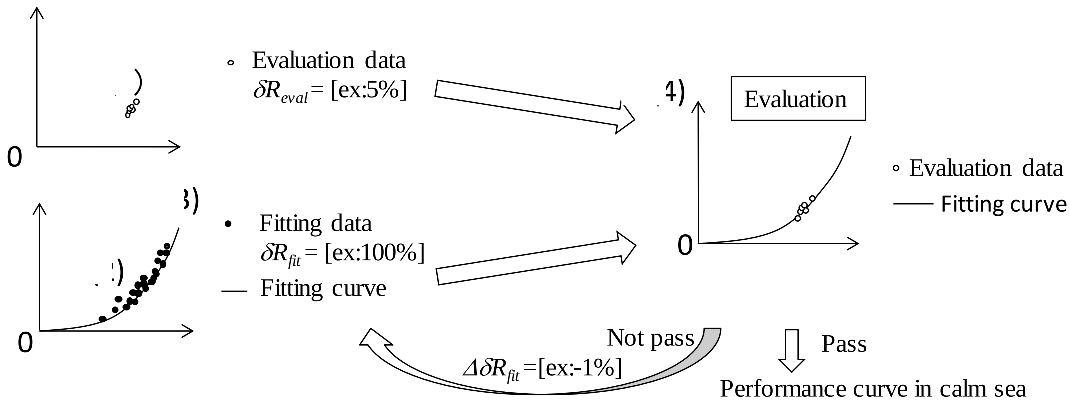

Fig.5: Outline of evaluation by increase rate of added resistance

On the first way, the data measured in the condition where waves and winds are negligible are extracted by much smaller δR (δR_{eval} in Fig.5) such as 5%. These data are used for the evaluation of the performance curve, which named 'evaluation data'.

On the second way, the data are extracted by large δR (δR_{fit} in Fig.5) such as 100% for estimating the performance curve in wide range of engine output which is required for the performance evaluation in lower output. These data are used for the curve fitting, which named 'fitting data'. Obtaining the fitting data yields the performance curve based on Eqs. (4) and (5), which is called "fitting curve".

$$N = d_{nv} \cdot V_S \tag{4}$$

$$P = a_n \cdot N^{b_n} \tag{5}$$

where V_S, N, and P is ship speed through water, engine revolution and power, respectively. a_n, b_n, and d_{nv} are coefficients for the fittings. After the two ways above, the fitting curve is evaluated in conjunction with the evaluation data. This evaluation is based on the data deviation around the fitting curve. The data deviation is expressed as DPC_{VP} which is defined by Eq. (6) using the number of the evaluation data N_{eval} and nominal distance d_{norm} (i) between the evaluation data and the fitting curve in the relationship between ship speed and engine output, *Sogihara et al. (2021)*.

$$DPC_{VP} = \sqrt{\frac{\sum_{i=1}^{N_{eval}} \{d_{norm}(i)\}^2}{N_{eval}}} \tag{6}$$

If DPC_{VP} is lower than the criteria, the fitting curve is recognized as the resultant performance curve of the OCTARVIA model. The criteria for DPC_{VP} are given 2.0. If DPC_{VP} exceeds the criteria, it is necessary to return to the second way with less δR_{fit}. The fitting data is re-extracted with the δR_{fit}, which provides new fitting curve and evaluated by the evaluation data. This process is iteratively conducted till DPC_{VP} does not exceed the criteria. If DPC_{VP} does not satisfy the criteria even after the iteration, the fitting curve obtained by the initial fitting data is output as the resultant performance curve.

4. Application to Ships in Service – Validation of Level-1

The OCTARVIA project phase 2 selected 14 ships for validating the effectiveness of Level-1 model as an equivalent model to Level-2 model. The selected ships are listed in Table III.

Table III: Selected ships in OCTARVIA project phase 2

Area	Ship	ID	Remarks
Domestic	Cargo ship	DCS	Instantaneous data is used for the validation. Engine power is calculated based on FOC.
	Cement carrier	DCC	Some items which are not collected in the onboard monitoring system are obtained from AIS data.
Oceangoing	Container ship 1	CS1	
	Container ship 2	CS2	
	Container ship 3	CS3	
	Container ship 3a	CS3a	Sister ship of CS3
	Container ship 3b	CS3b	Sister ship of CS3
	Pure car carrier1	PCC1	
	Pure car carrier2	PCC2	
	Bulk carrier 1	BC1	Panamax bulk carrier
	Bulk carrier 2	BC2	Panamax bulk carrier
	Bulk carrier 3	BC3	Cape-size bulk carrier
	Bulk carrier 4	BC4	Supramax bulk carrier
	Very large crude oil carrier	VLCC	

In the validation, ship performance curve in calm seas is evaluated according to the Level-1 model and Level-2 model, using onboard monitoring data collected in one year period. The result of the correction for wind and waves described in section 3.3 for PCC1 and BC3 is shown in Figs.6 and 7, respectively. These figures indicate that whether Level-1 or Level-2 is applied does not significantly influence on the correction. In other words, the correction based on Level-1 is equivalent to that based on Level-2.

The collected engine revolution and power is provided for evaluating ship performance in calm seas based on RCM. The evaluated performance curve (PC) in calm seas of PCC1 and BC3 is shown in Fig.8 and Fig.9, respectively. It is noted that, in Figs.8 and 9 V_{des}, N_{MCR}, and MCR denotes ship speed at design condition, engine revolution at maximum continuous rate, engine output at maximum continuous rate, respectively, and that "Evaluated PC" means the resultant performance curve of the OCTARVIA model. In this validation, the evaluation data is extracted with δR = 10% from the corrected data after the filtering by apparent slip ratio. Similarly, the fitting data for drawing the fitting curve is extracted with δR = 50% from the corrected data. Figs.8 and 9 show that, for both Level-1 and Level-2, extracting the evaluation and fitting data enables drawing the performance curve while it is difficult to obtain the performance curve based on all the collected data.

The engine revolution difference δN_{des} and engine power difference δP_{des} at V_{des} between Level-1 and Level-2 model is calculated by Eq. (7).

$$\delta N_{des} = \frac{N_1}{N_2} - 1 \qquad \delta P_{des} = \frac{P_1}{P_2} - 1 \tag{7}$$

where N_1 and N_2 is engine revolution at V_{des} evaluated by Level-1 and Level-2, respectively,
P_1 and P_2 is engine power at V_{des} evaluated by Level-1 and Level-2, respectively.

Fig.10 shows the difference between the results of Level-1 and Level-2 model evaluation. Except for DCS, PCC2, VLCC, absolute value of δN_{des} and δP_{des} is less than 2.0%. This indicates that, as long as ship performance evaluation complies with the OCTARVIA model, Level-1 and Level-2 model can provide equivalent results.

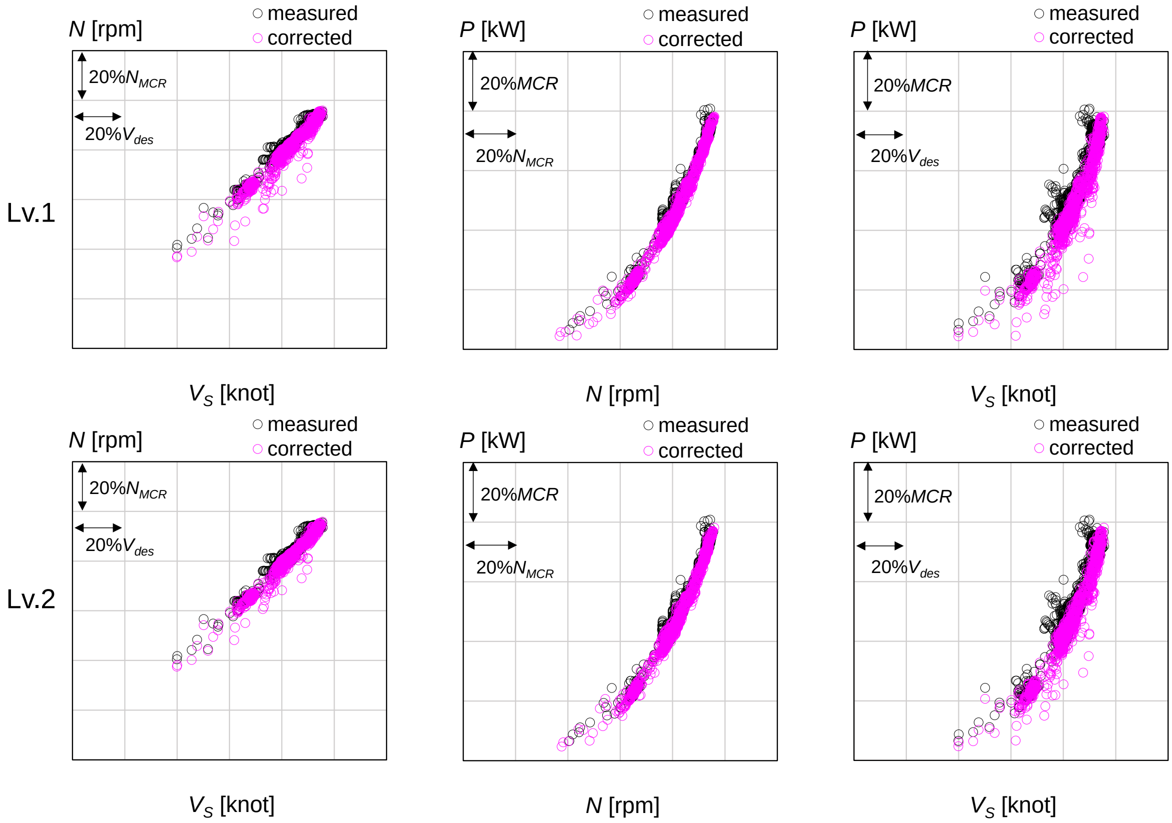

Fig.6 Correction of engine revolution and power. (PCC1, upper: Level-1, lower: Level-2)

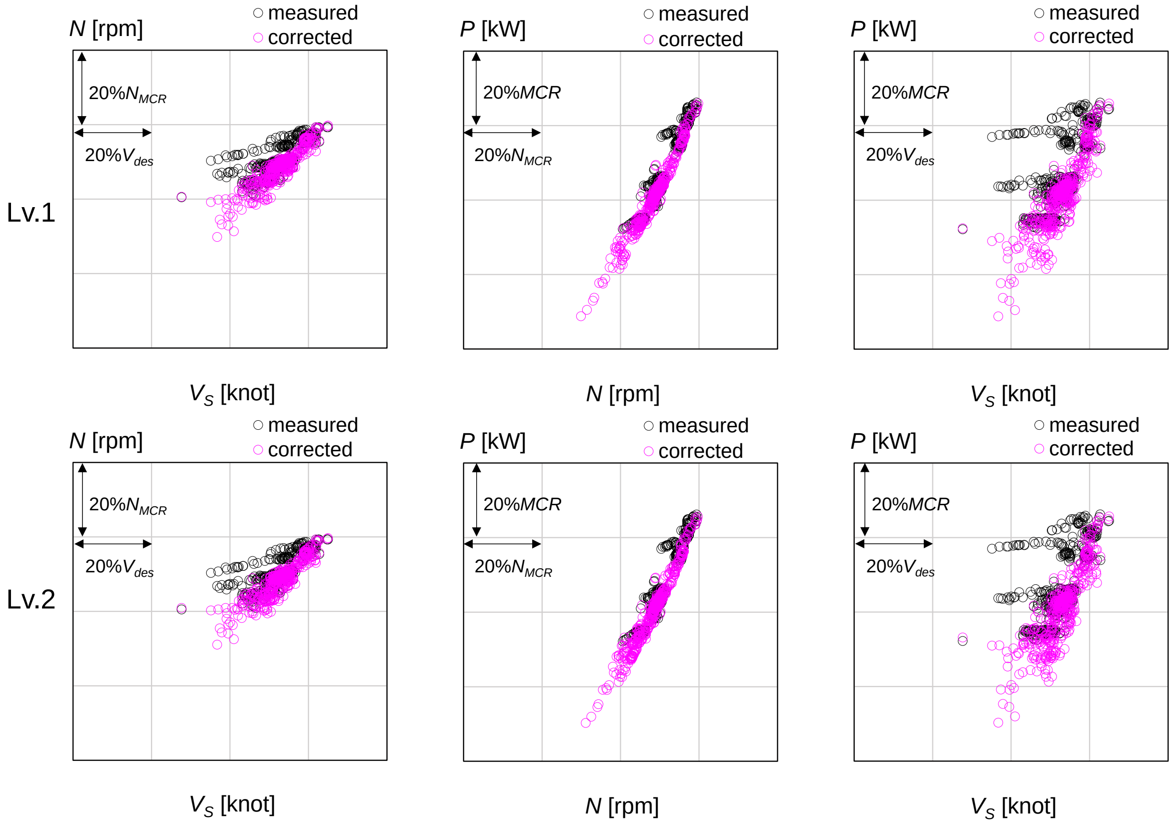

Fig.7: Correction of engine revolution and power. (BC3, upper: Level-1, lower: Level-2)

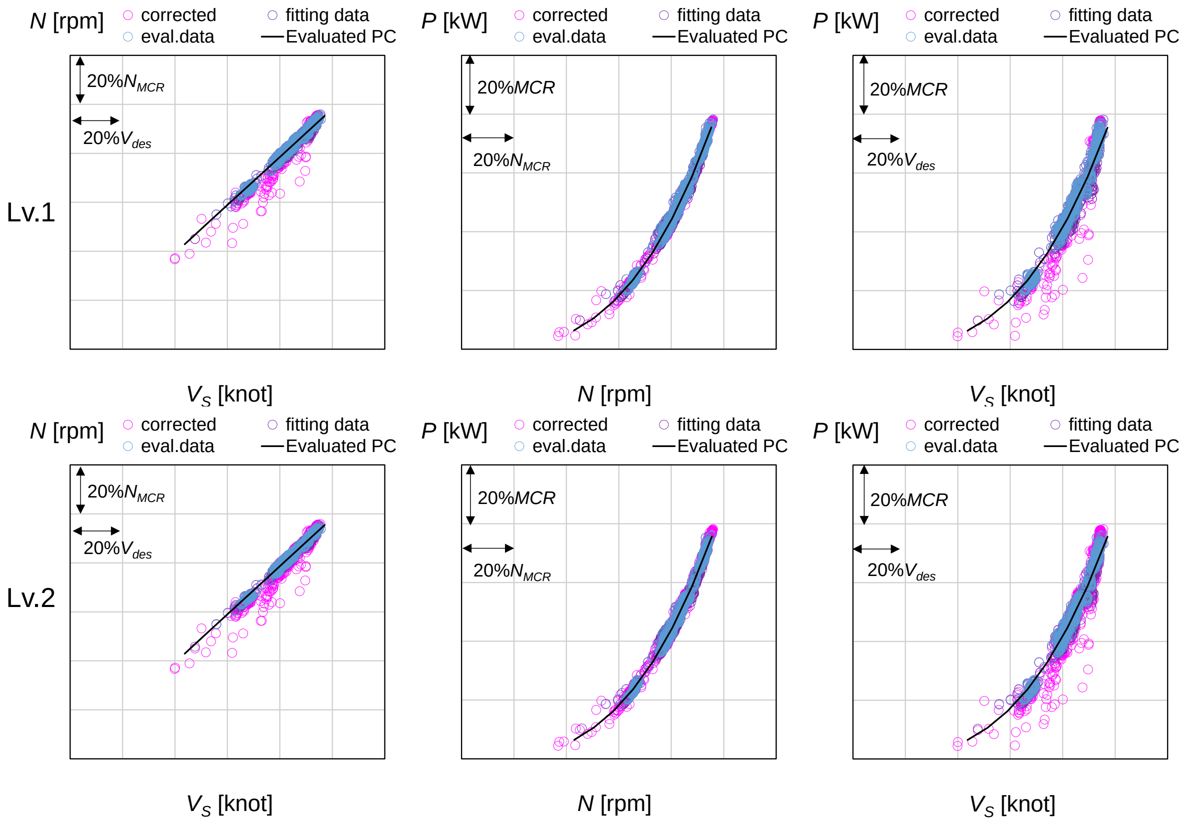

Fig.8 Result of evaluation of ship performance in calm seas. (PCC1, upper: Level-1, lower: Level-2)

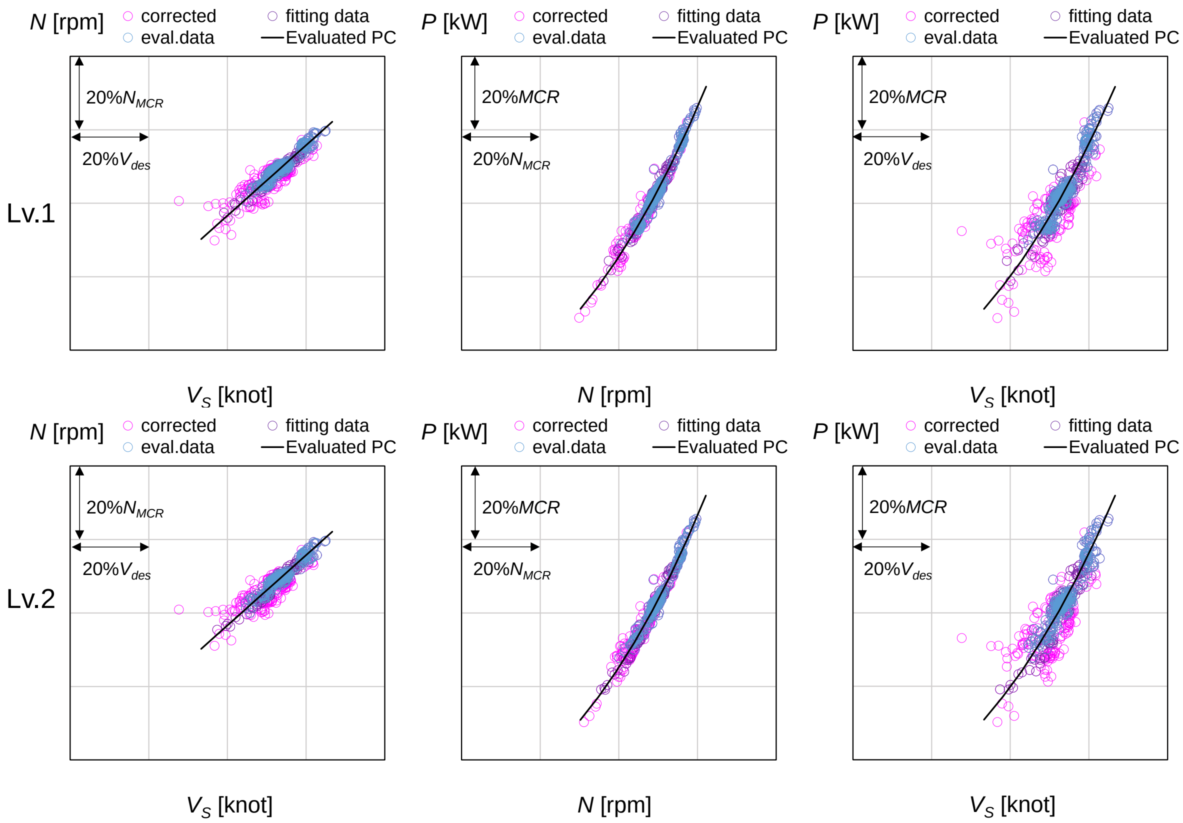

Fig.9: Result of evaluation of ship performance in calm seas. (BC3, upper: Level-1, lower: Level-2)

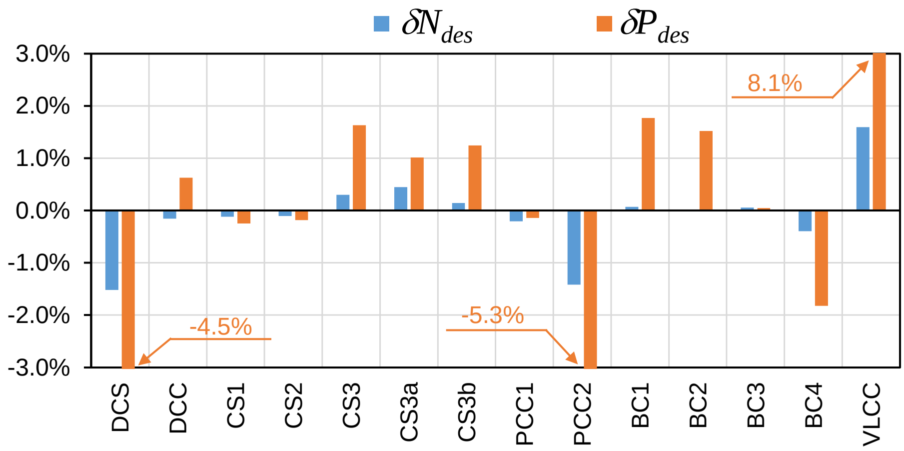

Fig.10: Difference between the results of Level-1 and Level-2 model evaluation

The large difference between Level-1 model and Level-2 model is observed for DCS, PCC2, VLCC. To make the OCTARVIA model robust, from what the differences are derived should be clarified. For DCS, the monitoring system provided instantaneous value, not mean value in a certain period, which gives dataset scattering in wide range. A use of instantaneous value can involve the effect of a fluctuation in time history. For evaluating performance of ships in steady condition, mean value should be used. In addition, DCS is not provided with shaft sensor, therefore engine power is calculated based on fuel oil consumption, which may bring engine power data with low accuracy.

Fig.11 shows DPC_{VP}; the deviation of the evaluation data around the resultant performance curve in the relationship between ship speed and engine power for the subject ships. While DPC_{VP} of Level-2 is about 2.5, DPC_{VP} of Level-1 is 3.3 which is much larger than that of Level-2. This implies that using instantaneous value as onboard monitoring data can bring poorly accurate results of the Level-1 evaluation. On the other hand, Level-2 evaluation is reliable approach even though the instantaneous value is used.

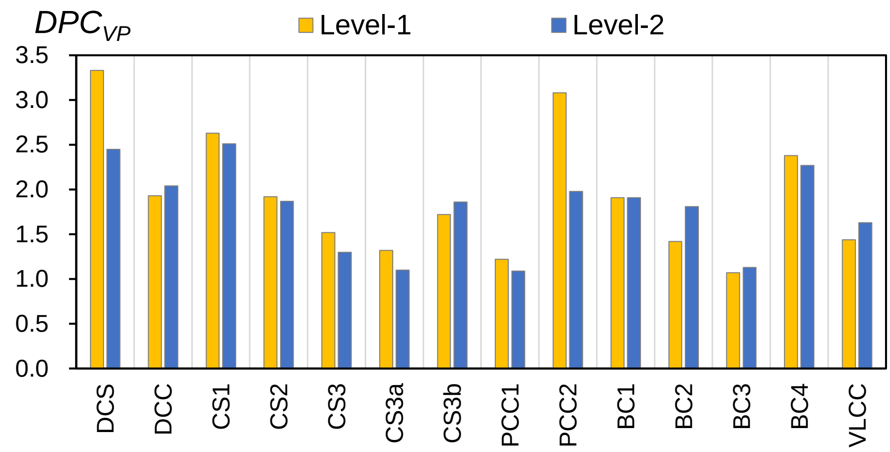

Fig.11: Data deviation DPC_{VP} for Level-1 and Level-2

Let us discuss on the difference in PCC2. In general, pure car carrier is strongly influenced on by wind. We tried to introduce the added resistance in wind of Level-2 evaluation in Level-1 evaluation, which indicated a good agreement between the models. This means that 5.3% difference in engine power is derived from the accuracy of the added resistance in wind, originated from superstructure parameters estimated in Level-1. Further, Fig.11 shows that DPC_{VP} of Level-1 is much larger than that of Level-2, which supposes that the larger data deviation results from the lack of the accuracy of the added resistance.

For VLCC, we conclude that the estimation of POC is insufficient for tanker. We also found that using POC of Level-2 in Level-1 evaluation indicates good agreement between the models. This implies that POC is not estimated accurately, and that, the inflow to propeller is not sufficiently obtained. Concisely speaking, self-propulsion factors is not estimated for tanker. The self-propulsion factors are calculated by the ship principal particulars in Level-1 using empirical formula based on model tests. We speculate that the subject VLCC is extrapolation of the model tests, which lead to poor estimation of the self-propulsion factors.

Although large differences between Level-1 and Level-2 model were obtained in three ships, Level-1 can be concluded to be equivalent to Level-2. The absolute difference in engine power at design speed is given averagely 2.0% for 14 ships and 0.9% for 11 ships other than DCS, PCC2, VLCC. Except the three ships, the data deviation DPC_{VP} of Level-1 model almost agrees with that of Level-2 model, which means that both the models can provide equivalent results of ship performance in calm seas.

5. Concluding Remarks

This paper introduces the ship performance evaluation model based on onboard monitoring data and two kinds of model: "Level-1 model" as a simplified model and "Level-2 model" as an accurate model. This paper also shows the comparison on the evaluation of ship performance in calm seas between Level-1 and Level-2 models for 14 ships in service. As a result, although low-accuracy appears in three ships, it is indicated that Level-1 model can evaluate the ship performance with equivalent accuracy to Level-2 model. The difference of the evaluated engine power at the design speed is averagely 2.0% for the subject ships. This means that a slightly incorrect estimation of the required parameters such as self-propulsion factors (specifically described in section 2) has little effect on the correction for wind and waves on the onboard monitoring data.

Using Level-1 model, ship owners or makers in shipping sectors (e.g., paint maker) can evaluate the ship performance with the equivalent accuracy as shipyards evaluate the ship performance. They can cooperate with shipyards in R&D for the reduction of GHG emissions from ships in accordance with the evaluation of the ship performance based on onboard monitoring data.

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Comparison of a Ship's Performance Before and After Hull Cleaning and Propeller Polishing

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Abstract

The most important question in deciding whether to perform a hull cleaning is "how much performance gain hull cleaning will bring?". In this paper, the performance of a ship before and after a hull cleaning and propeller polishing is compared. ISO 15016:2015 based method is used to analyse and compare the ship's performance at different environment. Then the difference in the ship's performance is quantified using ISO19030 performance values and indicators. The case study results will be used as a basis to build a model that predict the degradation during operation and performance gain after a hull cleaning and propeller.

1. Introduction

The performance of a ship, after being built, steadily decline during operation. After a period of service, for regulation requirements or a special need, it is dry docked for inspection and new painting to regain most its original performance. In between dry dockings, when there is a need to improve degraded performance, hull cleaning and propeller polishing are used. While the dry docking restores a ship's performance nearly to its original performance after being built, hull cleaning and propeller polishing can only restore a limited amount of the ship's performance.

The decision to perform hull cleaning and/or propeller polishing are made in several ways. The usual practice is to have an underwater inspection when a degradation of performance is noticed by the ship operator and if significant fouling is found, hull cleaning and/or propeller polishing are performed. There are also cases when hull cleaning is periodically performed or whenever after a ship is anchored for a significant period of time. A more optimal decision-making process will be by cost benefit assessment with cost of the hull cleaning versus expected decrease in cost by hull cleaning. However, there is not much quantitative data on the benefit of hull cleaning in terms of the ship performance. *Adland et al. (2018)* reported from a study of 8 aframax-size tankers that the reductions in fuel consumption are approximately 9% from hull cleaning and 17% from dry docking. This value will vary from ship to ship and environmental conditions in which the ship operates. Therefore, the decision for hull cleaning is still made based on experience rather than data.

In this paper, a method to compare the ship's performance before and after the hull cleaning is proposed with case studies of three vessels. The ship's performance is analysed by subtracting environmental effects due to wind, waves and difference in seawater density from measure power. The added resistance from wind, waves and difference in seawater density is calculated by method defined in ISO15016:2015, *ISO (2015)*, which is the standard method for estimating additional resistance during the speed trial of newly built ships. By subtracting added resistance, a ship's calm water performance is obtained and can be compared between before and after hull cleaning. In order to quantify the difference in a ship's performance, the concept of performance values and performance indicator in ISO19030-2:2016, *ISO (2016)* are used.

2. Performance Analysis Method

The performance analysis method is based on ISO15016:2015. First, un-processable data, such as when the ship changes direction or moving in shallow water, are removed by filtering. Then increases in resistance due to environmental forces are estimated by the method defined in ISO15016:2015. Then, these resistance increases are used to correct power using the direct power method as defined in ISO15016:2015. For the purpose of comparison, the analysis results are further corrected to standard displacement. The overall analysis procedure is summarised in Fig.1.

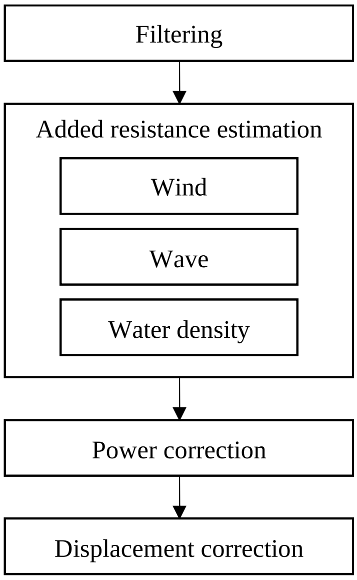


Fig.1: Performance analysis procedure

The purpose of filtering is to remove any extreme measurements to obtain data during steady cruising state. The filtering used in this paper is as follows:

- Remove when speeds are too low. Usually, the speed range in the model test is used as a reference and any data with the speed outside the range is discarded.
- Remove data when rudder angle is larger than 5° to remove when changing direction.
- Remove data when the ship is operating in shallow water.

Resistance increase due to wind, waves and differences in water density are estimated with the same method as used in ISO15016:2015. For wind resistance, ISO15016:2015 use the method as described in Annex C of ISO15016:2015. For wave resistance, typically there are no measurement data available. However, there exist publicly available wave data from sources such as the National Oceanic and Atmospheric Administration (NOAA). In this paper, STAWAVE II method in Annex D of ISO15016:2015 is used on NOAA data to calculate added resistance due to waves. *Lee et al. (2019)* has conducted validity study on the use of NOAA data against wave radar measurements and concluded that NOAA data provide enough accuracy. As this method can only applied for waves within ±45° of the ship's heading, other measured data points were automatically discarded. An increase in resistance due to differences in sea water density is calculated as detailed in Annex E of ISO15016:2015 from the water temperature, which is also available from weather services even if the ship is not equipped to record such data.

Once all resistance increases are estimated, they are used to correct the measured power value. The required correction for power is calculated using Eq.(1).

$$\Delta P = \frac{\Delta R \cdot V_s}{\eta_{Did}} + P_{Dms}\left(1 - \frac{\eta_{Dms}}{\eta_{Did}}\right) \tag{1}$$

where: ΔP is the required correction for power [W];
ΔR is the total resistance increase in [N];
V_s is the ship's speed through the water [m/s];
P_{Dms} is the measured delivered power in the operating condition [W];
η_{Dms} is the propulsive efficiency coefficient in the operating condition;
η_{Did} is the propulsive efficiency coefficient in the ideal condition.

ISO15016:2015 uses a load variation test to identify the ratio between the propulsive efficiency coefficient in the operating condition and in the ideal condition. However, as most ships does not perform a load variation test during a model test, if the results of the load variation test are non-existent, then ratio can be set to 1.

The corrected power is calculated by Eq.(2).

$$P_{Did} = P_{Dms} - \Delta P \qquad (2)$$

Where P_{Did} is the corrected delivered power in the ideal condition.

Each leg of the journey of an operating ship has different displacements, and to compare the analysis results, the difference in displacements must be considered. This is achieved by first defining standard displacements for typical loading conditions such as laden and ballast for bulk carriers and 80% or 90% displacements for container carriers. Then displacement difference between standard displacements and the actual displacements are corrected using the displacement correction method in ISO15016:2015. After displacement correction, analysis results can be compared with each other if they are the same loading conditions and even with the model test or sea trial results, if such data is available for the same loading conditions.

Analysis method and the software implementation are described in more detail in *Park et al. (2019)*.

3. Quantification of Performance Analysis Results

The performance analysis method in 2 results in a set of data points. While scatter plot of these points can give general idea of current ship's performance, a quantified value that represent the ship's performance is ideal. In this paper, the concept of performance values in ISO19030-2:2016 are used. For each data point, percentage speed loss is calculated by Eq.(3)

$$V_d = 100 \cdot \frac{V_m - V_e}{V_e} \qquad (3)$$

where: V_d is the percentage speed loss;
V_m is the measured vessel speed through the water;
V_e is an expected speed through the water.

The expected speed through water is obtained from a speed-power reference curve at the corrected delivered power. A speed-power reference curve can be obtained from either model test results or sea trial results.

The quantified performance of a set of data points then can be expressed as a simple average of performance values similar to performance indicators in ISO19030-2:2016.

4. Case Study

Three vessels are used for case study in this paper as summarised in Table I. The vessels are selected as their operation profile includes relatively long period of steady cruising and are susceptible to long term anchoring, which often result in performance degradation necessitating hull cleaning.

Table I: Vessels used for case study

Vessel	Ship type	Size
A	Tanker	110K DWT
B	Container Carrier	11000 TEU
C	VLOC	325K DWT

Table II describes data used with its source. The data used for performance analysis is readily available to most ships as they are typically measured during the ship operation except wave related data, which is not readily available to most ships. In this paper, wave data is obtained from publicly available NOAA data as described in section 2.

Table II: Data used for performance analysis

Data category	Data items	Source
Speed	Speed through water Speed over ground Speed of shaft revolution	Speed log GPS Shaft power meter
Heading	Gyro heading GPS heading	Gyro GPS
Power	Shaft power Brake power Delivered power	Shaft power meter Calculated from fuel flow meter
Wind	Wind speed Wind direction	Anemometer
Wave	Wind wave height Wind wave period Wind wave direction Swell height Swell period Swell direction	Wave radar Weather service provider
Temperature	Air temperature Water temperature	Thermometer

In the case study, the operational data for three vessels are collected. All three vessels experienced some measure of hull cleaning and/or propeller polishing during operation. Using performance analysis method described in section 3, operational data before and after hull cleaning or propeller polishing are analysed. The results are compared with each other to identify if performance analysis can be used in analysing the effects of hull cleaning or propeller polishing.

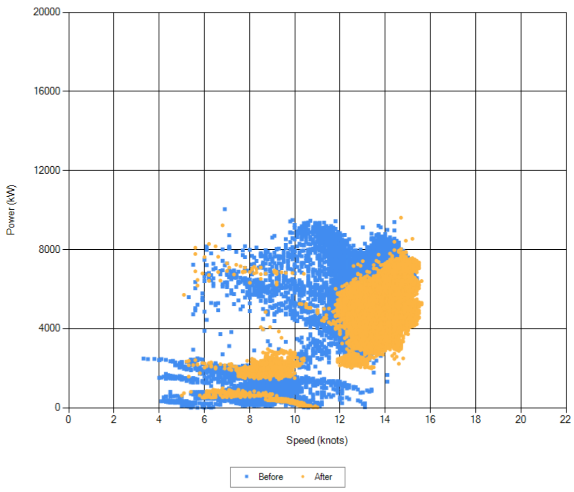
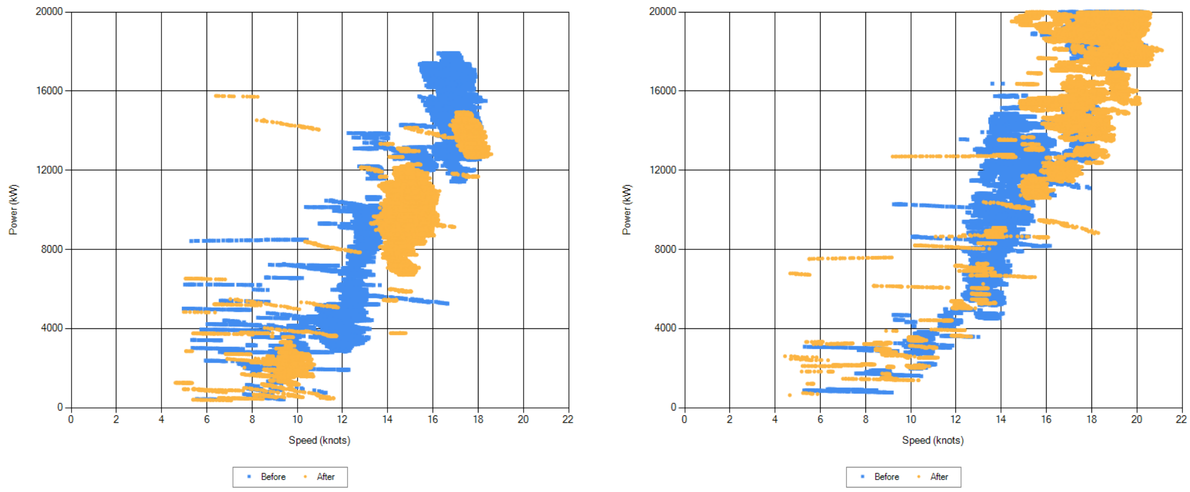


Fig.2: Performance analysis results of vessel A before and after hull cleaning and propeller polishing in ballast loading condition

In case of vessel A, a 110K DWT tanker, the operational data before and after hull cleaning and propeller polishing is used for the case study. As the performance analysis results clearly indicate in Fig.2, there are noticeable performance gain. The difference seems significant and in averaged percent speed loss, as shown in Table III is 6.78%. Hull cleaning and propeller polishing in this case is highly adequate.

In case of vessel B, a 11000TEU container carrier, hull cleaning and propeller polishing has been performed. As seen in Fig.3, there are also noticeable difference in performance between before and after hull cleaning and propeller polishing. However, the difference in performance seems smaller than in vessel A. The gain in averaged percent speed loss from hull cleaning and propeller polishing is 2.32% in design condition and 1.52% in eastbound condition. There are about 10% container load difference the two loading conditions, with the eastbound condition heavier of the two loading conditions.



(a) Design loading condition (b) Eastbound loading condition

Fig.3: Performance analysis results of vessel B before and after propeller polishing

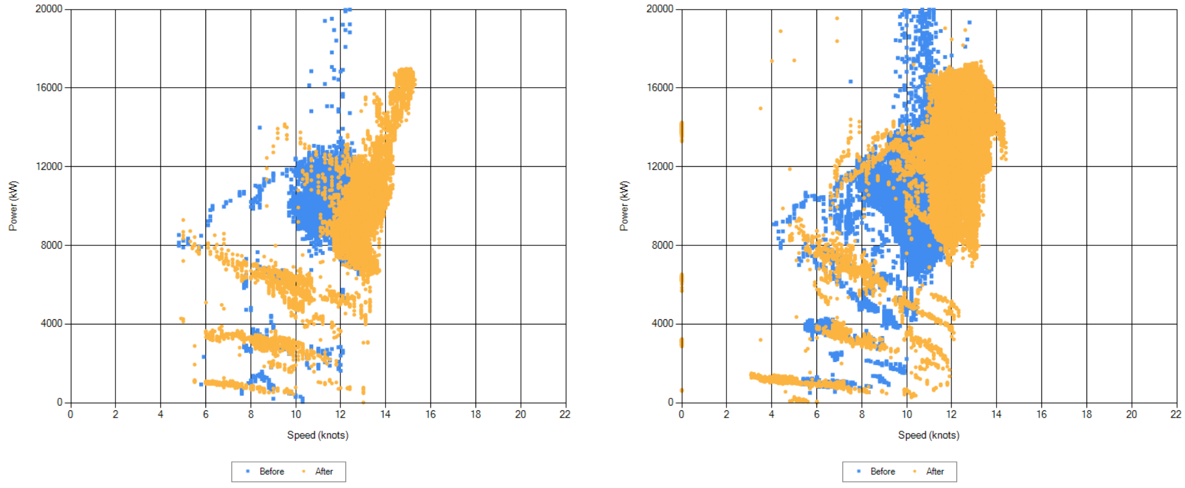
Smaller gain that other vessels can be explained by the condition of the hull before cleaning. As shown in Fig.4, the condition of hull before cleaning is good with only some slime/sea grass present in most part of the hull. Therefore, the effect of hull cleaning is minimal. If it had not been for high-speed nature of container carrier, full hull cleaning may not have been done.

(a) starboard side plate (b) port side plate (c) bottom plate

Fig.4: Vessel B hull condition before cleaning

In case of vessel C, a 325K DWT bulk carrier, hull cleaning and propeller polishing has been performed. Fig.5 shows the difference in performance before and after hull cleaning. In terms of averaged percent speed loss gain from hull cleaning, vessel B has the highest gain of three case studies with 8.17% gain for ballast condition and 5.39% for laden condition.

One noticeable fact is that the gain in ballast condition seems higher than in laden condition. This is also observed in case of vessel B in smaller scale as well. This is expected as heavier loading condition and more submerged underwater area and relatively smaller area of hull fouling compared to ballast condition.



(a) Ballast loading condition (b) Laden loading condition

Fig.5: Performance analysis results of vessel C before and after hull cleaning and propeller polishing

Table III: Quantified gain from hull cleaning and/or propeller polishing

Vessel	Loading Condition	Averaged Percentage Speed Loss		
		Before	After	Gain
A	Ballast	-0.59%	6.19%	6.78%
B	Design	-4.40%	-2.08%	2.32%
	Eastbound	-2.50%	-0.98%	1.52%
C	Ballast	-13.72%	-5.55%	8.17%
	Laden	-15.57%	-10.18%	5.39%

In all three case studies, performance analysis method used in this paper was able to show the effectiveness of hull cleaning or propeller polishing. However, this case studies are not enough to draw conclusions on the expected effects of hull cleaning or propeller polishing. As in vessel B, the effects of such measures are likely to be more dependent on the condition of hull and propeller before such measures are applied, and the results after their application. Therefore, in order to accurately analyse and predict the effect of hull cleaning and propeller polishing, other variables, such as the extent of hull fouling, should also be included for analysis.

5. Conclusions

In this paper, a performance analysis method based on ISO15016:2015 is presented and it is applied to three vessels to identify the performance gain from hull cleaning and propeller polishing. Performance analysis results are then quantified with averaged percent speed loss based on ISO19030-2:2016. The results shows clearly that the performance analysis method can be used to analyse the effects of hull cleaning and/or propeller polishing.

While this paper only presents three case studies, research is ongoing to investigate the relationship between hull conditions before hull cleaning or propeller polishing and the expected effects of hull cleaning or propeller polishing based on the performance analysis results. With more data available in the future, a model to estimate the effects of hull cleaning or propeller polishing can be built to aid in making decision on when and how often hull cleaning should be applied for optimal ship operation.

Acknowledgements

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The Arctic Tern: AI + Soft Values = Save Fuel

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Abstract

This paper summaries three years of technical development and research in close collaboration with several major shipping companies. Besides the technical AI-based decision support systems, the project has focused on soft values, how the support systems become efficient support for real, both ashore and onboard. It is important to create knowledge among technical-, commercial- and operation-departments within the organisations on how to implement new methods. Different types of vessels operate under vastly different commercial realities that impact the performance and energy effectiveness. Technical systems must be adapted to each actor's reality to achieve a change and drive more climate-friendly transportation. The Arctic Tern shows fuel savings of 2-14%.

1. Introduction

This is not the first time a new and innovative tool within "Weather routing" is introduced. AI is an impressive and efficient technique to handle large amount of data, but it is neither the first nor the last. For instance, wave models were introduced in the early 1990s, with a significant impact on what became possible at that time. This was followed by naval architect-based ship models that relied on noon reports and could calculate the impact of winds, waves, and currents on ships in the 1990s and early 2000s, using the best technology available at that time. When new models and systems for calculating ship movements and parametric roll were introduced around the same time, many in the industry believed this would revolutionise the market.

The advancements in weather and ocean current forecasts over the past 30 years, where the accuracy of long-term forecasts has greatly improved, have been crucial for enabling today's applications that rely not only on current but also future winds, waves, ocean currents, ship movements, and more. However, despite these advancements, the perception persists, even in academia in 2023, that forecasts beyond +72 hours are hardly considered useful.

10-20 years ago, client-based onboard systems for route planning gained widespread popularity. Now, these systems are partially being replaced by many even better online-based apps and other functionalities that offer high-quality (sometimes even free) weather forecasts. The visualisation of weather forecasts has also played a significant role. This proliferation has contributed to the increased trust in the forecasts among users onboard ships who have access to these modern systems today. Rightfully so.

In the 2020s, AI-based systems are being introduced to better optimise short and long sea passages for individual vessels and entire fleets. Ship models based on ANN (Artificial Neural Networks) and supervised machine learning are utilised. These models which rely on robust sensor data from the ship, collected every minute or even every 10 seconds. This has proven to be a groundbreaking development, surpassing previous methods in terms of accuracy and efficiency.

However, introducing new tools is not just about technical aspects. It also involves building trust and understanding of what the new tools actually can do and what they cannot. A broader understanding is needed throughout the organisation or the entire chain of actors who are all affected. Users of these now transparent systems come from different departments with different roles and expertise, both within their own organisation and others. These soft values and communication certainly involve the onboard team, the navigational and the engineering officers. But also includes the entire technical, operational, and commercial departments of the shore organisation, sometimes with watertight compartments in between, as well as additional actors in the customer or logistics chain. No longer is it solely the Master's responsibility to find the silver bullet for this issue. Even within traditional shipowner and charterer organisations, it is common for technological advancements to not immediately resonate with all individuals or the entire organisation. Both technology and people may need time to adapt to the change. Timing is crucial.

Ten years ago, there were approximately 10 service providers in the traditional weather routing/optimisation field. Around 5 of these were more prominent in bidding processes with major shipping companies. Today, there are hundreds of system providers that, in one way or another, "optimise" what is considered best, often using AI, today's state-of-the-art technology. Soon to be replaced by something new and more advanced.

Notably, several of these early prominent traditional service providers in weather optimisation at sea seem to struggle with building something new. Likely because innovation takes a lot of time and effort while maintaining and operating the existing 24/7 service is a heavy daily workload. It is much easier for start-ups to emerge and deliver. However, when today's start-up companies grow and eventually face a major technological generational shift, they are likely to encounter the same challenge. Many have experienced this journey, and more will undoubtedly follow.

Introducing new technologies on the global maritime market is one of NoorCares' core business. By actively exploring and testing new ideas and methods from a pragmatic perspective, NoorCare identify what works. Being receptive and understanding even the unspoken needs, regularly engaging with our valuable network of +60 shipowners/operators in Europe and Asia, as well as partners and competitors, is the key. This approach has been our practice for over 30 years. Additionally, contributing to the education of new captains and engineers by showcasing the latest market developments and gaining a better understanding of what the next generation of seafarers truly needs and expects allows further contribution to the future of maritime industry. It is an iterative process, and NoorCare are certainly still learning.

2. Background

For three years, the research and development project, The Arctic Tern, (Swe: Tärna) has been focusing on route optimisation using Artificial Intelligence. The project has been carried out by a consortium consisting of NoorCare AB, Möller Data Workflow Systems AB (Molflow), Linnaeus University, and the Swedish Maritime Administration. The consortium has extensive experience in sea voyage optimisation, both in theory and practice, from the perspectives of both the ships and the shore organisations.

Four reputable shipping companies, headquartered in Europe and Asia, took active part with vessels in the project. Three of these companies have fleets of 50 ships or more and operate both short and long sea passages across the world's oceans, representing both liner service and tramp shipping.

Molflow´s route planning tool, Slipstream, were set up and run by the shipping companies and Linnaeus University. Slipstream utilises multiple neural networks to estimate the vessel's performance. The networks are trained on ship data logs in combination with state-of-the-art Met-Ocean data that is collected multiple times every day. Slipstream continuously monitors the vessel's condition, including hull condition, and provides updated and precise status information. It has global coverage and considers factors such as tidal currents and water depths. The system includes Digital Twins for each vessel, accessible to users through a graphical user interface or via API. The optimisation tool also incorporates performance monitoring, including biofouling.

Energy efficiency and reduced environmental impact of shipping is a fundamental part of our shared responsibility to contribute to a better life on our planet for future generations for a long time to come. The optimisation tool Slipstream is based on machine learning and unique solutions that can use significantly more details and parameters compared to the traditionally available tools that dominate the market. This enables a new way to frequently be updated on the optimal result of any operation or machine settings that is the best considering all small and large changes that occur during the voyage. This is especially important for shorter sea passages where the traditional and less precise tools are rarely useful or relevant.

Alongside with the technical development of the AI-based support system, a large part of the project has been focused on soft values and the challenges the traditional and commercial drivers in international shipping meet. The focus has been on ensuring that users understand how the new precision tools should be used, preferably in combination with other already existing systems. Within the Arctic Tern project NoorCare has trained both the teams on commercial ships and the land organisation on how to better use new data. People with long practical experience. The Arctic Tern project has also carried out practical experiments for aspiring ship officers to become better equipped for the increasing demand of energy efficient sea transport before they start their professional career. The Arctic Tern project shows how a transparent and precise tool can be used for the whole organisation to obtain energy-efficient sea transports, for shorter as well as longer voyages, with a reduced environmental impact. The NoorCare Advicory concept shows results of fuel savings/reduced emissions between 2-14%.

Table I: Fuel savings indicated in the The Arctic Tern project

Type of vessel	**Sea passage length**	**Fuel saving**
Liner service	1-2 days	10-13%
Liner service	2-6 days	2-4%
Liner service	10-14 days	10-14%
Crude oil tankers	+20 days	3-5%
Students experiments at The Maritime Academy (Liner service)	10-12 days	12-25%

3. Soft Values – Our strength in combination with AI

One of the most crucial aspects of succeeding in energy efficiency can be summarised as attitude and willingness. Add perseverance and you may reach or even exceed your goals. This applies not only to the personnel onboard but also to the entire shore organisation within a shipping company and the surrounding maritime cluster that influences the vessel's chartering and port logistics.

3.1. Introducing Innovation to the Maritime Industry - The devil is in the details

Artificial Neural Networks (ANN) with supervised deep learning, including a naval architect ship model, are, truth be told, a black box where it is not always clear why the results turn out as they do. You may accept the result, but not always fully understand. In some situations, you may understand more afterwards. That's learning. With old technique, it was necessary to filter out a significant amount of data points before plotting a graph based on a few points only. Assuming a robust flow of data from sensors, AI can handle a large amount of data with multiple precision and efficiency, which is remarkable. Even so, it is crucial to understand the bigger picture and be able to distinguish significant information from trivial - from the customer´s perspective.

For a larger high consuming vessel on shorter sea passages, minor unplanned deviations, such as a half-hour engine stop, can easily disrupt the optimisation of a smooth shaft power and completely negate the intended fuel savings since they are of the same magnitude as what is needed to compensate for the lost half-hour or so. Similarly, a delay due to unexpected traffic congestion in a busy area like the Singapore Strait can have the same impact on the energy consumption. Also, such details as a large vessel requires time for acceleration and deceleration at the beginning and end of the sea passage will affect the detailed setting of the system. The squat effect in shallow water, all examples of things that were never an issue during longer deep-sea passages, can suddenly become highly relevant and sometimes decisive. On a longer sea passage, there is often enough time for things to even out before the vessel reaches its destination. This can also apply to the end of a long voyage when regular or daily monitoring requires more details towards the end of the passage to be accurate. It is a different perspective to consider more details and have the ambition to reduce unnecessary margins when appropriate. The handling of modern precision tools, therefore, differs from what many have learned over the years.

So even though with the new tools, decimals are handled to diligently save fuel and reduce emissions, suddenly something bigger can disrupt everything, such as a very poor weather forecast or diversion to a new destination. Or just a modified piece of information about when the berth that is being aimed for will be available.

3.2. Learning by Doing - Towards more Climate-Smart operations

Personnel onboard and ashore that use the result from an AI-based tool like Slipstream must be given the opportunity to understand the tool and critically review the results. They should be allowed to use it sensibly, experiment, and sometimes fail in order to learn. They should be able to feel involved in a larger process with a common direction. As a next step, based on the new experiences and conclusions, new Standard Operating Procedures (SOPs) can be established with the aim of finding the efficient method that best suits the specific organisation.

In the Artic Tern project, experienced captains occasionally discovered and questioned the results of Slipstream. For example, before a voyage with unusual draft/trim, Slipstream had never been trained on such extreme loading data and simply did not know how the ship would behave, despite being based on supervised deep learning and having a ship model in the background. On another occasion, a completely different ship was going to round South Africa for the first time. The digital twin, the model for this particular ship was not trained on the very long and high swell from abeam, resulting in the output not matching reality. In practice, the ship rolled more than what the untrained Slipstream had calculated, and the speed was consequently lower. In both cases, the model learned quickly after the first passage and new data from the sensors automatically trained the ANN. However, it was important for the project to prevent similar mistakes from happening again for any other ship at any other time. And there are some good methods to ensure that this never happens. But the truth is that the more reliable data you have, the better the results will be. The amount of reliable data is crucial.

But AI and machine learning can be so beautiful when they provide new detailed explanations and insights. For example, when the model helps discover and explain details in a specific ship's behaviour in varying wind and sea conditions from the stern. Behaviours that both the captain and an experienced marine meteorologist previously attributed to "perhaps some minor variation in the ocean current," due to a lack of better explanations. Or the example where it's finally possible to measure/quantify biofouling in a way that traditional methods based on noon reports and old-school mathematics have never quite succeeded in despite more than 20 years of work. But with good AI tools and reliable high-frequency data, this is suddenly achievable.

These and many other examples build genuine and solid trust in new detailed AI-based tools like Slipstream. When users gain trust in how the new precision tool works, they can more easily reduce their margins in a different and improved way compared to before. By transparently sharing this information throughout the organisation, the risk is distributed, whether it's either some excessive fuel saving or the just-in-time performance not being entirely perfect. In an encouraging and tolerant corporate culture, it becomes natural for the Master not to bear the entire responsibility alone. As is often still the case today.

3.3. The NoorCare Advisory concept

The NoorCare Advisory concept has been demonstrated and "tested" at numerous shipping companies, with the ambition to encourage more shipowners and charterers to find methods for operating in a more environmentally friendly manner that suit their specific needs. It is striking how significant the differences are between different shipping companies with the same types of ships and similar operating methods, depending on where they are in the process. Often, the realisation is that robust high-frequency data must first be generated before moving on to the next step. The International Maritime Organisation's latest global regulations regarding EEXI and CII, as well as the European Union's new ETS (Emission Trading System), which will be implemented in 2024, are all in line with the current transformative process for the entire industry. All opportunities and contributions that help society move towards even better energy efficiency and completely ceasing the release of carbon dioxide into the atmosphere are welcome. The expectations for the industry to deliver are increasing.

There are today thousands of vessels that still rely on traditional suppliers in weather routing. Many of them do so out of tradition, even though they often need only a small portion of the traditional and partly outdated concept. Many shipowners and charterers are also in a transition period, where they realise they would benefit from an upgrade of at least some of their used methods/ algorithms/ systems. But time is a valuable asset, and the market offers a wide range of options, and it is now harder than ever to distinguish between excellent and subpar providers and solutions.

3.4. The Shipping Industry's future decision-makers

Within the Arctic Tern project, three cohorts of students in the maritime captaincy program have been able to use Slipstream during a real-time project voyage between Gothenburg/Sweden and New York/US, during winter season.

It can be summarised that the system has provided good decision support on how to set the speed considering the current weather, forecasts, and the required ETA given to the students.

The students who frequently performed updated optimisations achieved the lowest fuel consumption and minimised environmental impact. It was also noted that the students who used Slipstream instead of solely relying on conventional methods based on available weather data were able to carry out the project voyage in a significantly more energy-efficient manner.

4. Conclusions

AI-based route optimisation systems with ANN and supervised machine learning for ships that have robust and high-frequency sensor data are a prerequisite for more detailed calculations/ optimisations of set values for speed and machinery.

These modern and much more precise tools for faster and easier decision-making regarding speed and engine settings for a particular vessel on a specific route with an unique loading condition are highly significant for the ability to operate ships more energy-efficiently and in a climate-smart manner on a broad scale.

Introducing these AI-based decision systems into shipping has significant similarities to the introduction of previous groundbreaking technologies over the past thirty years, primarily targeting the ship's captain.

The similarity lies in the fact that it takes time to build trust and understanding among users regarding what the new optimisation system can or cannot do. People need time to adjust.

The difference in introducing AI in the 2020s is that there are more people involved in the onshore organisation, and the systems today are more complex. Small changes during the sea passage can have a greater impact on the results when current margins and tolerances are streamlined.

The Arctic Tern project deliberately selected some vessels/companies that have commercial conditions that make it significantly more challenging to save fuel compared to many others.

1. Large container ships in liner service, on short sea passages of 2-6 days, in a part of the world where it is practically almost impossible to obtain a reliable berth slot time closer than 1-2 days in advance. During the same sea passage, the required ETA and thus speed can vary anywhere between maximum and min/eco speed, sometimes multiple times.
2. Crude oil tankers on the spot market, on long voyages for several weeks across the world's oceans, where the commercial aspect requires that speed and fuel consumption on a 24-hour basis are within very tight ranges. Therefore, it is almost never possible to optimise the entire sea passage.

Both examples illustrate different instances of "Hurry up and wait" behaviour deeply ingrained in the shipping companies because it is the best way to make money. At least it has been so far. Despite this, the project demonstrates fuel savings. Of course, the savings would have been even greater without these commercial realities.

Knowing when the berth at the destination port will become available already at commence of the sea passage (1) and replacing the outdated Charter Party contract system with a more transparent and reliable system that creates sufficient trust for both shipowners and charterers (2) are two things with enormous potential for significant energy efficiency improvements in maritime transportation.

It is also desirable to introduce more industry standards and common regulations that facilitate all service providers in creating and encouraging “proper behaviour" regarding overall energy efficiency and smoother traffic flow. This can facilitate better interaction between different systems and thereby reduce the number of stand-alone systems. It may involve the format of route exchange, class-approved methods for calculating ships' expected impacts on weather and traffic situations, common standards for acceptable safety levels or risks at sea, in the ports, and at the terminals etc. This may help ensure that the Safety-Environment-Economy requirements within the maritime and transportation sectors develop in a harmonious balance between feasibility and desirability.

Calculating and optimising a single sea passage and thereby contributing to smoothing out the traffic flow between Port A and Port B is relatively straightforward in this context, especially now in 2023 with systems based on the latest technology, including AI, Artificial Intelligence.

Acknowledgements

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Savings as Expected? - Guidance Towards a Successful Benefit Tracking Process of Propulsion and Hull Improvements

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Abstract

This paper shares experience obtained from many retrofit processes to support shipping companies on their journey towards an ideal ship operation. IMO emission regulations and high fuel prices encourage shipping companies to optimize ship efficiency. Luckily several retrofit technologies are available to make the best out of a ship. Usually, model basin tests or CFD techniques are used to determine the impact on the EEXI and estimate the savings. While in operation deviations between expectations and actuals can still occur. This paper points out things one should be aware of when planning Hull & Propeller Improvements. Furthermore, guidance is given to assess the impact of the technologies successfully over time.

1. Introduction

1.1. Background

The recent developments in the global and regional regulatory frameworks, such as the IMO emission regulations and the EU ETS, as well as the societal pressures for environmental sustainability, have and will continue to increase the cost of energy. To keep their fuel cost under control, shipping companies are reconsidering their vessel efficiencies through operational change and vessel upgrades. More broadly, improving vessel efficiency is a key strategy to comply with the greenhouse gas emissions regulations, and achieve one's decarbonization goals.

Although Maritime transportation is already one of the most efficient modes of transport it remains that its contribution to the global GHG emission is large while opportunities for improvement are readily available. As shipping company engage in ever larger vessel upgrade projects, their ability to accurately define the benefits of these projects is key to provide the necessary transparency for future investment decision and ultimately allow for the IMO target to be met.

1.2. Why the opportunities for improvement are large

Several factors have led to the relatively large optimization potential of vessels:

- Operation different from intended design point: Vessels are designed to run at a given main engine power, but due to the fuel efficiency measures of the last decade they are often running on significantly lower engine loads. Sailing on higher loads is nowadays also no longer an option as compliance to the new Energy Efficiency Existing Ship Index (EEXI) is achieved frequently by an Engine Power limitation (EPL) or a Shaft Power Limitation (ShaPoLi). While vessels operating at lower power level certainly limit their fuel consumption, these off-design conditions create inefficiencies that can be addressed.
- General development of existing technologies: Improvements have been made concerning the main engine and propeller efficiency within the last decade. Apart from many smaller measures the main engine efficiency was improved through higher bore vs. stroke ratio. Lower RPMs and Computation of Fluid Dynamics (CFD) have allowed propeller makers to improve their designs and reach higher propulsion efficiencies.
- New technologies: The recent advances in maritime engineering have led to the emergence of several innovative technologies that have transitioned from theoretical concepts to practical applications. One such technology is the air lubrication system, which employs air bubbles at the flat bottom of the ship to reduce frictional losses and enhance fuel efficiency. Another

example is the revival of wind power as an alternative energy source, facilitated by devices that require minimal operational effort.

1.3 Defining your approach

IMO has set up through the Glomeep project a website, https://glomeep.imo.org/technology-groups/, where one can learn more about Energy saving Devices (ESDs) available on the market. Beside this, many marine societies like the Baltic and International Maritime Council (BIMCO) or the Maritime Cluster Northern Germany (MCN) have issued guideline documents concerning different energy efficiency technologies available to the industry. These guidelines can give shipping companies a first overview of technology options available to them.

When ship operators decide upon retrofits, they will usually heavily rely on the fuel consumption reduction as a basis for ESD benefit evaluation. Other side benefits derived from vessel retrofitting (maintenance, manoeuvring, equipment lifespan, etc.) are typically assessed qualitatively only. Apart from the pressure imposed by GHG regulations, the requirements of sound business cases to justify investment in ESDs remain. These and the promised savings should however always be reviewed with some care and more, *Bertram (2020)*.

2. Know the condition of the vessel

2.1. Sea Trial vs. actual performance

Knowing the current vessel performance and the propeller light running margin is important before the propulsion setup is modified as this will have an impact on the retrofit design and saving potential. The EEXI is related to the Sea Trial performance of the vessel. ESDs often proven through CFD calculations and their impact and this can be considered in the EEXI calculations. It is usually expected that the same impact will be found on the operated vessel. However, vessels often operate at different engine load conditions compared to when the vessel was built and went on sea trial. This is due to both hull and propeller fouling and the natural aging process of the hull and propeller, such as wear and tear of the structure of the vessel due to sea impact over time. Even when the impact of fouling can be reduced through the application of a new paint, there should not be an expectation that the vessel would be back to her sea trial condition after a dry-docking.

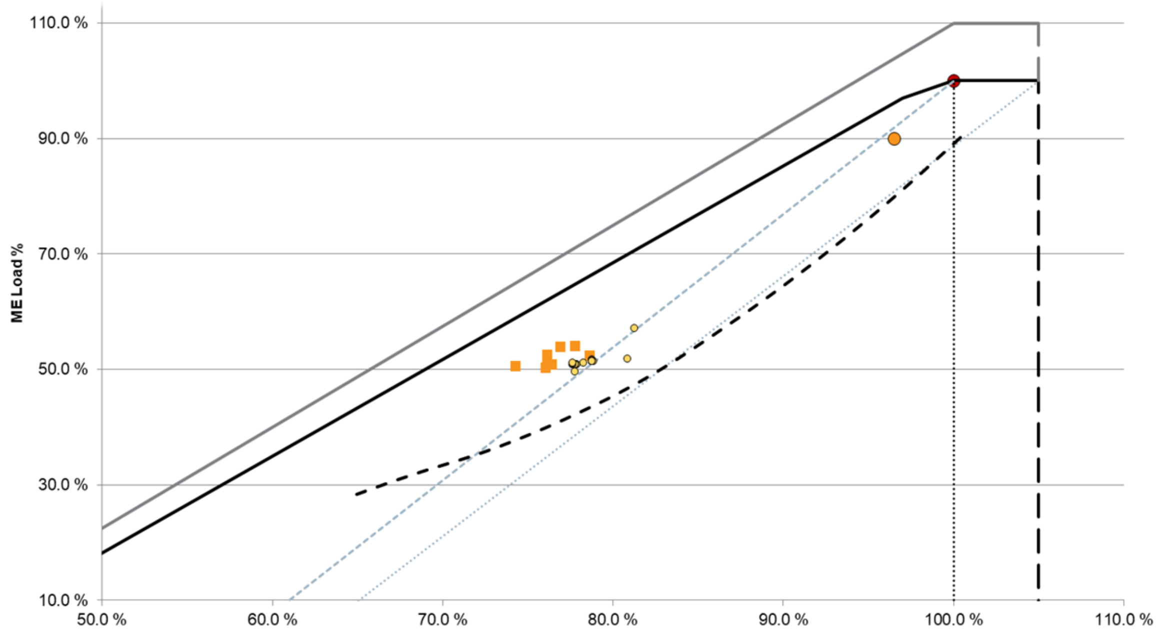

Fig.1: Main engine diagram with operational data and Design Propeller curve (before & after installing a pre-swirl device)

Fig.1 shows the main engine diagram of a vessel in Ballast condition. Operational data before the retrofit (yellow round dots) and after the retrofit of a pre-swirl device (orange dots) is shown. The black dashed line shows the propeller curve at Sea Trial condition.

One can observe that the vessel was running far from the propeller curve before the retrofit and the installation of the pre swirl device has increased this issue. In general, heavy running conditions of the main engine and propeller should be avoided due to a worse specific fuel oil consumptions and worse propulsion efficiencies. Overall, one should not expect fuel savings when the vessel operation has changed as shown in Fig.1.

Replacing the propeller, changing the pitch of the existing propeller or changing its diameter can fix heavy running issues and ensure that the engine and propeller run in healthy conditions. The cost of these solutions varies and should be considered prior to a vessel upgrade as part of a complete propulsion system optimisation.

2.2. Consider the Service Margin of the vessel

During the design phase of a vessel, the effects of hull fouling and added weather on the vessel propulsion are considered through the Service Margin, also known as Sea Margin. This margin is typically an arbitrary value of 15 % of the installed main engine power, *MAN (2023).* It can also be set higher depending on various factors like the sailing region, the dry-docking intervals and the type of vessel operation, *Ghose and Gokam (2004).*

The general approach of using 15% can lead to differences between vessel types when considering how much Service Margin remains under normal operation. Table I lists the additional weather power requirements for BF 4 head weather, computed according to ISO 15016. The resulting actual Service Margin is compared between a handy bulk carrier and a container vessel of a similar size.

Table I: Service margin according to ISO 15016 for container vessel and bulk carrier of similar size

Vessel & resistance details	**contianer vessel**	**bulk carrier**
LOA	177.6 m	180.0 m
LPP	167.6 m	173.0 m
Breath	27.0 m	29.8 m
DesignSpeed	16.9 kn	14.5 kn
BF4 $R_{wind\ Head}$	63.6 kN	47.4 kN
Seastate 4 - R_{Wave}Head	46.1 kN	68.2 kN
Pweather (etaD = 0.7)	1362 kW	1232 kW
Comparision of Service Margin	**container vessel**	**bulk carrier**
Installed ME Power	12600 kW	6780 kW
Service Margin of 15%	1890 kW	1017 kW
Percentage of Service Margin used at BF 4	72.1%	121.1%

The predicted propulsion power to overcome the weather forces is somewhat similar between the vessels, whereas the installed main engine power of the container vessel is much higher than at the bulk carrier. As a result, the bulk carrier has less additional power to overcome weather impacts. Noting that the biofouling likelihood is also higher for slow vessels with long idle periods, typical of bulk carrier operation, the likelihood that such vessels operate in heavy running conditions is high.

The Service Margin and the corresponding Light Running Margin of the engine and propeller are important factors that ship owners must quantify and compare with historical data. This requires the availability of quality data since the last dry-docking. In the absence of valid data, the decision should rely on the current ratio of rpm to torque of the main engine and its deviation from the sea trial conditions.

Operating condition exhibiting excessively high torque demands may require creating a new reference period of the propulsion performance after resolving this issue, typically with a new paint and potentially postponing the decision concerning ESDs until the outcome of the dry-docking about the actual operation condition of the vessels hull and propeller is understood.

2.3 High impact of paint performance

The biggest impact on the hull & propeller performance is usually imposed by the paint and antifouling condition. The paint performance is dependent on various factors and can vary enormously considering the fouling likelihoods of different operational profiles. Knowing the paint condition and how the paint performance has developed over time matters. Different paint types will show different performance characteristics within a dry-docking cycle.

After a dry-docking, some paint technologies require a certain time span before reaching their top performance whereas other paint technologies have their peak performance right from the beginning. Fig.2 shows a comparison of different paint models, i.e. technologies, over time and the performance indicator Excess Power percentage. Paint 1 has a high polishing effect and needs in this graph more than a year before reaching its top performance. Paint 2 has a low polishing effect but, overall, worse performance than Paint 1. Paint 3 does not have this polishing effect. The shown sample vessel had a polishing paint similar to paint 1and is currently performing quite well.

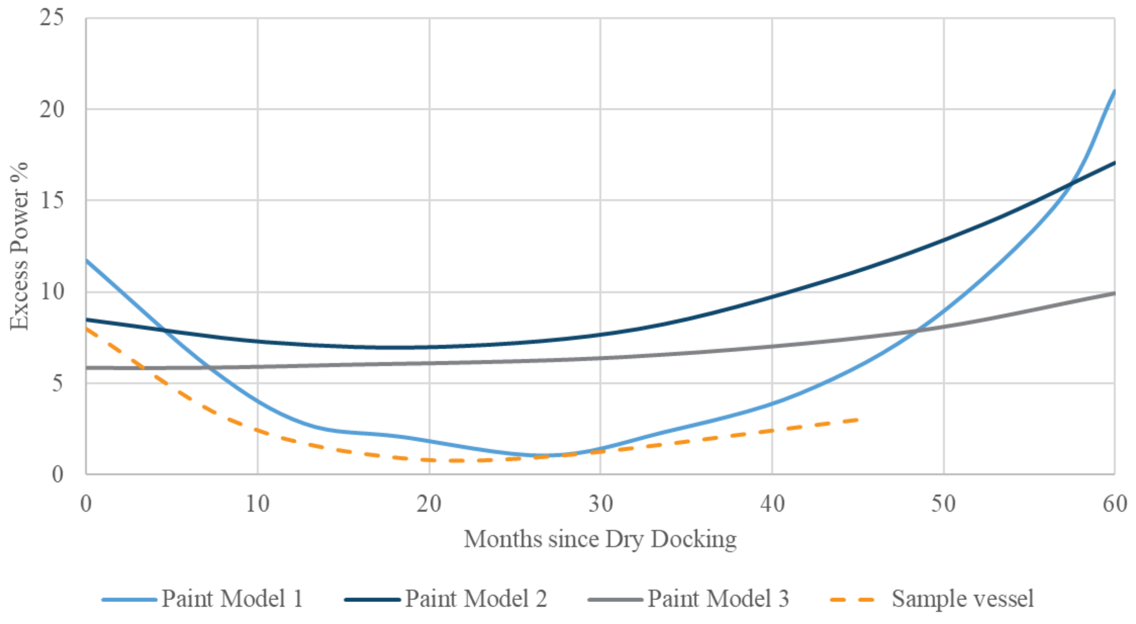

Fig.2: Comparison of different paint models and a sample vessel

A hull and propeller retrofit is mostly done during a dry-docking with a new paint implemented as well. So in this section a dry-docking event is understood to include a new paint application. When considering an ESD installation outside of the dry-docking cycle, on should be aware that the development of the paint performance can overrule the impact of a retrofit. At the sample vessel in Fig.2, for instance, it is not advisable to conduct an early dry-docking simply as the current paint performance is very good. Applying a new paint and installing a retrofit with a marginal propulsion improvement could lead to overall higher fuel consumption as the new paint may take time before reaching the same performance levels.

Shipping companies and paint providers should cooperate and analyse how far the vessel is deviating from the expected performance before decisions upon ESD installations outside of the dry-docking Cycle are made. Poor performing vessels can then be cleaned or receive a new paint along with the ESD installation. Whereas well performing vessels should only be retrofitted outside of the dry-docking Cycle at cases where the expected level of improvement through the ESDs is significant.

3. Measure with care

3.1. What can be measured considering the levels of accuracies

If specific Energy Saving Device claim benefits above single digits fuel reduction, most remain well below 5% of the total vessel consumption. In addition, to what can often be considered marginal improvement, the commercial cases for these investments are often hanging on the balance for a fraction of those claimed benefits.

In that context, it is important to remain realistic about our ability to measure fuel savings as such. From noon report to modern high-frequency data collection system, the ability and the required timeframe requirements to evaluate ESD varies greatly. The accuracy levels of the measurements and the tracking capabilities of shipping companies in general are often not in line with the accuracy expectations of the investors and decision makers.

Noon reporting systems are widespread in the maritime industry and provide snapshots of the vessel parameters on 24-hour intervals. These systems enable long term review of the vessel performance and fuel consumption. Provided that the noon report data is entered with care and subject to validations and reviews, effects on propulsion efficiency of about 5% and more can usually be tracked in these systems. ISO 19030 indicates 4.57% accuracy for noon reports based on observed speed and power derived from fuel consumption (95% confidence interval and for a 6-month evaluation period), *ISO (2016)*.

A challenge is that it takes long time to get sufficient analysis data, based on which further decisions could be made. The 24-hour sampling rate also does not allow the review of transient ESD such as wind assisted propulsion systems, or generally any device affected by external factors such as environmental conditions that vary in much shorter timeframe.

On the other hand, a continuous high frequency data monitoring system is by no mean a silver bullet, as such systems have their own challenges, such as reliability of sensors and the requirement to develop skillset not traditionally present within a shipping company. Still, as per ISO 19030, high-frequency monitoring allows much better accuracy and significantly better granularity The effect of certain ESDs simply cannot be tracked without having a high-frequency monitoring system.

According to ISO 19030, the average error is 0.37% for such system based on measurement of speed through water and engine torque (95% confidence interval and for a 6-month evaluation period). However, these accuracy figures assume that all is working well. In reality, this is not always the case. In practice, propulsion efficiency improvement can hardly be tracked with an accuracy of ±1%.

3.2. Using performance indicators

When assessing the impact of an ESD, using the milage of the vessel as it is done at the Carbon Intensity Indicator (CII) is not appropriate. An average milage assumes a linear relationship between the speed and fuel consumption, physically this is not the case.

The objective of any retrofit benefit tracking process is to conduct a fair comparison between the pre-retrofit and post-retrofit conditions. This necessitates the availability of quality data for both periods, as well as the proper application of propulsion performance indicators.

A hull performance indicator is a measure that compares a filtered and corrected observation with a baseline. For example, ISO 19030 uses Percentage Speed Loss as a hull performance indicator, but there are other methods or indicators that can also track the changes in Hull and Propeller Performance over time. Each of these indicators has its own advantages and disadvantages.

Table II lists different performance indicators we have seen in practice. The selection of performance indicator depends usually on vessel type, measurement equipment, operational model, and ESD to be evaluated.

Table II: Performance indicators with advantages and disadvantages

Performance indicator	Description	Advantages	Disadvantages
Percentage Speed Loss	Used in the ISO 19030 standard. The vessels speed is compared to the theoretical speed of the baseline model. Zero percent would mean that the vessel performs as the baseline model.	- Well documented. - At vessels operate on constant power or cons. RPM, it makes sense to look at speed change.	- Speed differences cannot be converted directly into power/fuel/USD
Speed Percentage	In essence this is the same method as "Percentage Speed loss", the difference is that not 0% is the baseline, but 100%	- Same as percentage speed loss	- Same as percentage speed loss
Excess Power Percentage	The propulsion power of the observation and the baseline are compared. The percentage expresses the excess amount of propulsion power.	- Usually torsion meters are more accurate than fuel meters. - Percentage can be translated easily into Fuel Consumption & USD	- Can be more scattered when vessels operate on constant power than speed percentage.
Excess Consumption Percentage	The propulsion related fuel consumption, so most often the main engine fuel consumption of the observation and the baseline are compared. The percentage expresses the excess amount.	- Can be translated very easily into financial impact (USD)	- Fuel meters are often not very accurate. - No separation of main engine and propulsion performance
Added Resistance Percentage	The measured propulsion power is converted into frictional resistance. This value is then compared to the frictional resistance value of the baseline model.	- Physically hull fouling effects the frictional resistance. This is physically more correct, when focusing on biofouling reviews of hull and propeller.	- Requires high quality baseline models. - Vessel specific conversion needed to relate to fuel consumption & USD
Consumption equivalent at a given Speed	The idea behind this performance indicator is to use the excess consumption percentage to estimate what the fuel at a given speed would be. Then this fuel consumption in t/24h is plotted over time.	- Charterers and owners can directly see how far away they are from the charter contract terms.	- Same as Excess Consumption Percentage - This value does not quantify how far away from optimum the vessel is.
Apparent Propeller Slip	Apparent Slip = RPM * Pitch - Speed-Through Water, so it is the difference between the measured engine distance and the speed through water.	- No baseline model required. - RPM measurement available on the most vessels.	- Hardly possible to convert to Fuel Consumption & USD - Only works for 1 draught - No weather corrections - Only the relative value over time should be used.
Admiralty constant	In the admiralty formula the ratio between power and speed is assumed to be cubical and between power and draught to have an exponent of 0.666. With these assumptions the admiralty constant can be determined for each observation.	- No baseline model required.	- This value does not quantify how far away from optimum the vessel is. - Rough reference model. Often too far from reality.

3.3. Selecting the right reference periods

The evaluation of the achieved improvements is impacted by the reference period used to analyze and quantify the previous vessel operation condition. How the reference period needs to be chosen depends on the several factors:

- Type: What kind of retrofit should be tracked? (Hull and propeller retrofit including paint or excluding paint? Can the retrofit be turned on and off?)
- Data validity: Have the measurement methods (sensors, reports) or reference models changed? Is there a need to consider other effects?
- Sufficient data: Is the reference data statistically sufficient to draw a conclusion?
- Operation: How have the operation conditions and the sailing area changed?

When selecting the reference period one must avoid that the change of the vessel fouling condition overrules the performance analysis outcome. ISO 19030 suggests comparing the average performance indicators post previous dry-docking to post retrofit dry-docking. This is a feasible approach, when the vessel was painted along with the retrofit installation and the expected overall paint characteristics are similar. Fig.3 shows the data periods that should be compared in such a situation.

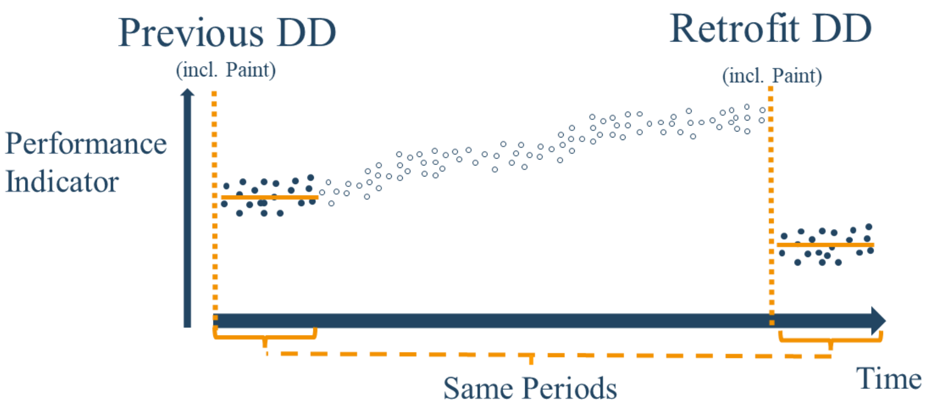

Fig.3: Dry-docking (DD) (or berth) to dry-docking

The challenge with this approach is the availability of valid data after the previous dry-docking as that data must have been gathered 5 years ago. Collecting, integrating, pre-processing and storing data for performance monitoring purposes on existing vessels is not trivial, *Baur (2016)*. Furthermore vessels may change their owners within a period of 5 years and the operational data is not always transferred to the new owner.

If data after the previous dry-docking is not available, then using the data after the last hull and propeller cleaning should be considered. By this one would at least compare clean vessels and mitigate the paint effects to a certain extent. In cases where such data is also not available or where the vessel was not painted, the data just prior to the dry-docking needs to be taken. Either way how and why the reference period was chosen impacts the computed saving and shall be communicated clearly between all stakeholders.

3.4. Expect that only one retrofit can be assessed per event

ESDs concerning the hull and propeller performance can typically be installed only during the vessel's dry-docking events. For this reason, these ESDs are often installed in combination with a new paint when the vessel is docked. Since Paint performance models discussed in chapter 2.3 are yet too inaccurate to allow a separation of the benefits, the saving cannot be separated between the new paint and the new propeller and only the combined saving can be tracked. This also applies when multiple ESDs are deployed during a single dry-docking.

This rule does not apply for ESDs which can be switched on and off. These are for instance wind assistance devices or air lubrication systems. One can turn the systems on and off and compute the difference in performance.

3.5. Review the dependencies of the chosen performance indicator

The operational profile of a vessel can change drastically depending on market condition and associated vessel income potential. Fig.4 shows the operational profile of a large container vessel after previous dry-docking and after the retrofit dry-docking. A noticeable difference in the sailing speeds and draughts of the vessel can be observed between the reference period and the period after the retrofit.

Before retrofit

Speed [kn]	Draught [m] 8.0	10.0	12.0	14.0
9.0	0%	0%	0%	0%
11.0	0%	0%	0%	0%
13.0	0%	1%	1%	0%
15.0	0%	1%	2%	2%
17.0	0%	2%	9%	7%
19.0	0%	4%	14%	9%
21.0	0%	4%	19%	10%
23.0	0%	1%	8%	4%
25.0	0%	0%	1%	0%
27.0	0%	0%	0%	0%

After retrofit

Speed [kn]	Draught [m] 8.0	10.0	12.0	14.0
9.0	0%	0%	0%	0%
11.0	0%	1%	2%	0%
13.0	1%	4%	11%	3%
15.0	0%	3%	11%	7%
17.0	0%	3%	9%	10%
19.0	0%	1%	5%	11%
21.0	0%	0%	3%	9%
23.0	0%	0%	1%	3%
25.0	0%	0%	0%	0%
27.0	0%	0%	0%	0%

Fig.4: Operational profile of a large container vessel before retrofit (left) and after retrofit (right)

Fig.5 shows the performance indicator, Speed Percentage, over draught for a sample data set of a container vessel. A light draught dependency of the Speed Percentage can be observed. The Speed Percentage is computed slightly higher for lower draughts. Such dependencies mean, that the performance indicator becomes less reliable as an assessment metric. Propulsion power baseline models which are not ideal will have speed or draught dependencies of the performance indicator. Apart from the baseline model this has to do with the used weather correction models, *Schmode et al. (2018)*.

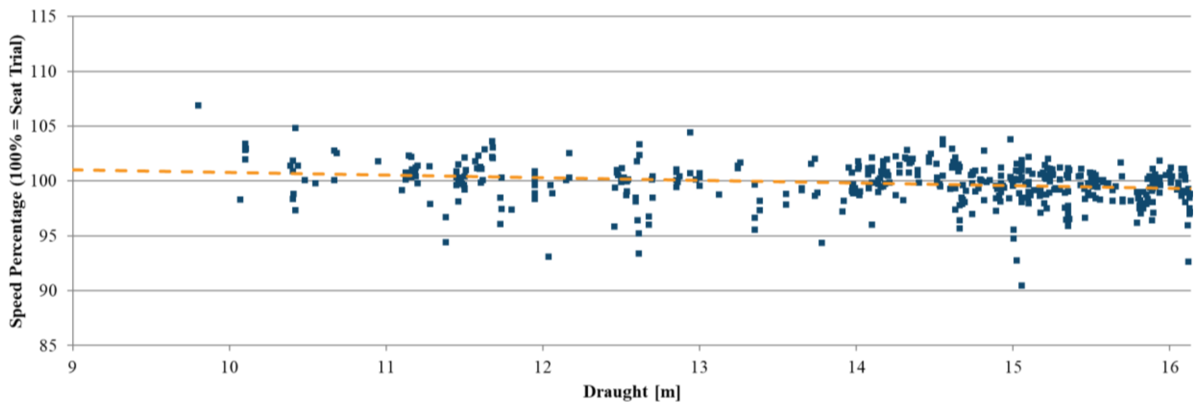

Fig.5: Speed Percentage value over draught to analyze the draught dependency

The significant change of operational profile together with a speed and draught dependent performance indicator led at the sample container vessel of Fig.4 to a lower saving outcome than it was initially expected. In this particular case the reason was however not that the ESD was underperforming. The vessels baseline model was incorrect and after correcting for speed and draught dependencies a saving similar to the expectation could be computed.

Most performance baseline models are based on Sea Trial observations and, as the Sea Trial has a very limited operation band, extensive extrapolation is done to create the reference model. There is a need to review with data how far the set reference model is reflecting the propulsion performance of the actual vessel for different sailing conditions, *Marioth and Raj (2021)*. Poor models may lead to misinterpretation of the results.

3.6. Demonstrating success – Time matters

In the context of a ship upgrade investment, it is important to achieve alignment within the various stakeholders on the ability to demonstrate the improvement benefits claimed. The time it takes to gain certainty on a retrofit success is often underestimated. The achievable levels of accuracies are well described in ISO 19030 considering different type of measurement technics. Beyond that the following points should be considered when setting expectation:

- The technical refinement required for measurement:
  Some devices like Mewis duct or PBCF do not require device specific measurements, but most advanced ESDs influence multiple aspects of the vessel energetic ecosystem. As an illustration, an air lubrification system will both increase the auxiliary engine load to operate and reduce the propulsion fuel consumption. When data is collected from multiple sources, it should be expected that the relative time to get to a suitable of accuracy is increased as the data signals from all sources need to be valid and a tracking scheme needs to be put in place.

- The variation in vessel operating profile:
  Even when using proper performance indicators, it remains that a vessel operating on specific route at fairly constant loading condition will provide a more constant basis to assess the benefit of an ESD against. In contrast to this a more varied operating profile will require further investigations and this often leads to a longer period of review to reach a conclusion.

- The transient nature of the savings:
  Where a traditional ESD such as a duct may provide a constant improvement in propulsion efficiency for a given operating speed and therefore fuel saving, a wind assisted propulsion contribution will vary over time. This will again increase the period of evaluation required to meet a given level of accuracy.

Efforts should be made to create awareness within the organization that it takes time until reliable conclusions can be drawn, in particular when the measurement frequency is as low as in a noon reporting system.

4. Review your expectations

4.1. Review the expected savings considering the actual operation profile

Any business case is created with a certain expectation about the financial impact to the business. For ship operation this means that one needs to make an estimate of the fuel consumptions that the vessel will have as well as the operational profile of the future. After the installation of the retrofit the vessel will be operated depending on the new market conditions, which can lead to a different operational profile. This simple fact is visualized in Fig.6. When a saving is not reflecting the expectations then either the impact on the propulsion performance was estimated incorrectly or the operational profile itself has changed. It is recommended to review the business case of a technology by computing the expected savings considering the actual operational profile and compare this to the original business case before a conclusion is made on how well a technology deliver on its promises.

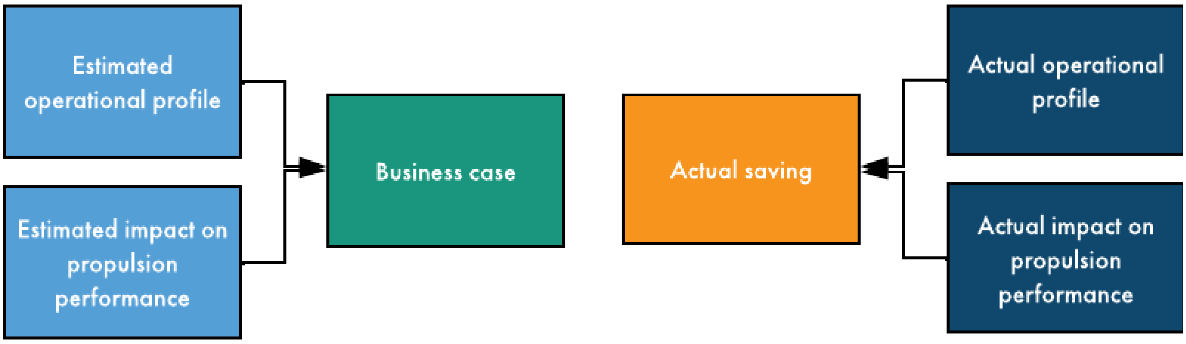

Fig.6: Business case vs. Actual saving

4.2. Do not underestimate the crew's contribution

One of the key factors for the successful implementation of ESDs on a ship is the human factor. The crew members are the ones who operate and maintain the ship and its equipment, and their actions and attitudes can have a significant impact on the performance of the ESDs. It is essential to train the crew in order to ensure that the ESDs installed delivers on their energy improvement promises.

Beyond training, developing crew engagement also requires taking their feedback and addressing any potential barriers or challenges that may hinder their acceptance or adoption of ESDs, such as:

- Lack of trust: The crew may not trust the ESDs reliability or their suppliers, especially if they have had negative experiences with similar devices in the past or when it leads to other complications.

- Change of work patterns: The crew may be reluctant to change their work patterns or routines, especially when they perceive that an ESD may lead to additional resource pressure.

- Fear of losing control: The crew may feel that the ESDs reduce their autonomy or authority over the ship, especially if they perceive them as intrusive or restrictive.

By training, introducing feedback sessions and engaging the crew, the shipowner can ensure that the ESDs installed on the ship are used optimally and effectively, and that they continue to provide consistent and sustainable energy savings over time.

4.3. Leverage additional savings by reviewing the operation

In general, it is assumed that a vessel will be operated with the same operational profile and operational speeds, no matter how efficient it is. This is a simplification, as ship operators often have processes in place to optimize the operational earnings of their vessels.

The retrofitted vessel will be subject to an optimization process as well, depending on how ship operators balance emissions vs. commercial operations, either the financial savings are slightly higher, but the emission improvements are not as good as predicted or the savings are lesser and the emissions are even better. More efficient vessels have an overall higher level of flexibility when operating.

5. Conclusion

This paper aims to provide some insights on how to leverage vessel data to guide a vessel retrofit process and measure its outcome. The skillset underlying the points outlined in this document are not traditionally present in vessel operators' teams. This can lead to both an over reliance on ESDs suppliers provided information and some difficulty in undertaking a thorough assessment of the benefits provided by such equipment.

In addition, as the maritime industry sets itself ambitious decarbonisation target, the need to integrate the constraints associated with vessel upgrade good practice to well established vessel life cycle should not be underestimated.

Decisions upon ESD installations needs to be made taking the actual condition of the vessel into consideration. This can be done by analysing and sharing valid operational data of the hull and propeller with the ESD suppliers and ensuring that the propulsion condition of the vessel is understood sufficiently by all parties. After that a decision upon the best modification of a vessel can be made.

Acknowledging the limits of our ability to measure and prove the savings of ESDs after installation it remains that with finite investment capability our industry needs to give itself the means to make decision based on established facts. In this regard shipowners should evaluate whether experience and data can be shared beyond a case-to-case basis amongst each other. This will help to identify technologies that provided the most significant benefits and operate the fleets most efficiently.

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From Big Data to Small Models:
Building a Generic Vessel Performance Simulator

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Abstract

In this paper we present a simple hierarchical approach for modeling the fuel consumption of vessels in different weather and operational conditions. Our model is fitted on fuel consumption data collected from a pool of vessels in the Wärtsilä database, and vessel-specific sub-models can be derived from this underlying generic model based on the vessels' characteristics only. In other words, fuel consumption can be modelled even for vessels with no fuel consumption measurements. We validate the approach using vessel specific data collected by Wärtsilä and show that even though the fuel consumption predictions for a single vessel in absolute terms will not be as accurate as they would for a corresponding data full model, the relative impact of different external conditions can still be reasonably well captured. Moreover, the accuracy of fuel consumption predictions increases when aggregating predictions over multiple vessels. For these reasons, the model can be useful for leg performance analysis or weather optimization, but also for fleet fuel consumption or emissions estimation based on AIS data for example.

1. Introduction

A vessel's fuel consumption depends mainly on its speed through water but also on various weather conditions such as wind speed and waves and operational conditions such as draft or stabilizer usage. To analyze the performance or optimize the operation of a vessel during a leg, we need a model that is able to take into account all these relevant factors. Typically fuel consumption data either in the form of (high frequency) measurements or via noon reports is required for the vessel in question to build such a model. Unfortunately, this type of data may not always be available.

Modelling vessel fuel consumption based on a combination of high frequency data and noon reports has been considered in *Antola et al. (2017)* and *Deymier et al. (2021)*. Here we first employ a similar methodology to build fuel consumption models for a large sample of vessels. Then, we combine this ensemble of individual models with corresponding data on vessel characteristics and generalize this information to create a single generic fuel consumption model that can be applied even for vessels outside the original sample. In this sense, our approach takes after the hierarchical propulsion power model introduced in *Solonen at al. (2021)*, however, it does not admit to the Bayesian formulation.

The main benefit of the hierarchical approach, also known as multilevel modeling, is that the resulting generic model can be used to predict fuel consumption without any fuel consumption data from the vessel to be modelled. Instead, we just need the vessel's characteristics, that are typically available from different online databases or even from the shipowner directly. In this sense the model can be called data-free. Input data includes the vessel speed information (that can be obtained from the AIS signal), weather information (from forecast), depth information for the squat effect and information on possible operational choices like draft and stabilizer usage.

It is evident that different types of vessels have different speed-fuel curves, and they also react to the various external conditions differently. Including more of the vessel specific information in our model allows us to account for these differences more accurately. On the other hand, we may also improve on the model accuracy simply by increasing the number of external conditions that we account for. In other words, when tuning the accuracy for our generic fuel consumption model, we have two dimensions we can play with: the selection of vessel characteristics and the relevant external effects. Experimenting with different choices we may try to find the most relevant factors in each dimension and the right balance between these two dimensions.

We note that in general we cannot expect the same degree of accuracy from a data-free model as we would from a corresponding data-full model (i.e., one fitted on the vessel's own fuel consumption data). For instance, hull fouling alone has a significant impact on the fuel consumption that is hard to capture based on observable characteristics only. Nevertheless, a data-free model may still be sufficient for the purposes of leg performance analysis or weather optimization, where the relative impact of different external conditions matters more than the overall fuel consumption in absolute terms. Moreover, if the sample used to train the data-free model is representative of a larger population of vessels, then the prediction accuracy should improve when aggregating predictions over multiple vessels. Hence, we may use the model to estimate fuel consumption or emissions of an entire fleet.

2. The generic fuel consumption model

Here we present the hierarchical vessel fuel consumption model. Instead of following the Bayesian formulation in *Solonen at al. (2021)*, we merely employ simple statistical relationships to describe the dependence of the model parameters on vessel characteristics.

2.1. General framework

Let us consider a generic fuel flow model that for an individual vessel i takes the form

$$f_i = f(\boldsymbol{v}, \boldsymbol{x}, \boldsymbol{\theta}_i) + \varepsilon_i, \quad (1)$$

where f_i is the fuel flow of the ship, $\boldsymbol{v}$ is the velocity through water, $\boldsymbol{x}$ is a vector containing information about all other relevant external conditions (such as current, wind, sea state, water depth, draft, and number of stabilizers out), $\boldsymbol{\theta}_i$ is a vector of vessel specific parameters and ε_i denotes the modelling error. Many existing models such as the STEAM2 model in *Jalkanen et al. (2012)* or the fuel flow model considered in *Antola et al. (2017)* fit into this framework.

When specific fuel consumption data for vessel i is available, the model parameters $\boldsymbol{\theta}_i$ (1) can be directly estimated via statistical regression. However, when such data is not available, we need to resort to alternative means. In white box models, such as STEAM2, the parameters are evaluated from explicit formulas. Here we take an alternative approach and estimate the parameters based on fuel consumption data collected from a large pool of other vessels. The underlying assumption is that the parameter values are close to each other for vessels that are similar in terms of a given set of observable characteristics $\boldsymbol{c}_i$. In other words, the parameter vector can be estimated as

$$\boldsymbol{\theta}_i = \boldsymbol{\theta}(\boldsymbol{c}_i) + \boldsymbol{\eta}, \quad (2)$$

where the estimation error $\boldsymbol{\eta}$ is reasonably small. The goal is now to find such a function $\boldsymbol{\theta}$ using individual fuel consumption measurements from a large enough number of vessels. The set of observable characteristics $\boldsymbol{c}_i$ can include for instance vessel dimension, vessel type, gross tonnage, construction year or information about the engines or propulsion and auxiliary systems.

Once the relationship $\boldsymbol{\theta}$ is known, we obtain the final fuel flow model for the vessel i simply by combining the Eqs.(1) and (2). The predicted fuel flow $\hat{f}_i$ is then given by

$$\begin{aligned} \hat{f}_i &= f(\boldsymbol{v}, \boldsymbol{x}, \widehat{\boldsymbol{\theta}}_i) \\ \widehat{\boldsymbol{\theta}}_i &= \boldsymbol{\theta}(\boldsymbol{c}_i). \end{aligned} \quad (3)$$

2.2. Example: Fitting a simple model

In the following we use high frequency data collected over a two-month period from a total of $N = 98$ cruise vessels and aggregated to 15-minute frequency. The mass flow rates have been measured with flowmeters installed onboard and then normalized with respect to the calorific value of the fuel type being used. For speed through water, we have used values obtained by adding the sea current forecast (provided by Tidetech) to the speed over ground measured by GPS.

As an illustrative example, we consider a very simple fuel model of the form

$$f_i = a_i v^3 + b_i + \varepsilon_i, \qquad i = 1, \dots, N. \qquad (4)$$

We first estimate the parameters a_i and b_i for each vessel separately with simple linear regression for the Eq.(4). We then examine the relationship between the obtained estimates and the vessel length (between perpendiculars) l. In Fig.1 we have plotted the estimated values for the parameters a_i and b_i as a function of l_i^k, where $k = \frac{3}{2}$. From these plots we obtain the relationships

$$\begin{aligned} a_i &= \alpha l_i^k \\ b_i &= \beta l_i^k. \end{aligned} \qquad (5)$$

From the plots we have filtered out some outliers where the vessel specific fits are unrealistic (fuel flow has no dependence on v). Using the generic model, we can find somewhat sensible values for these vessels as well.

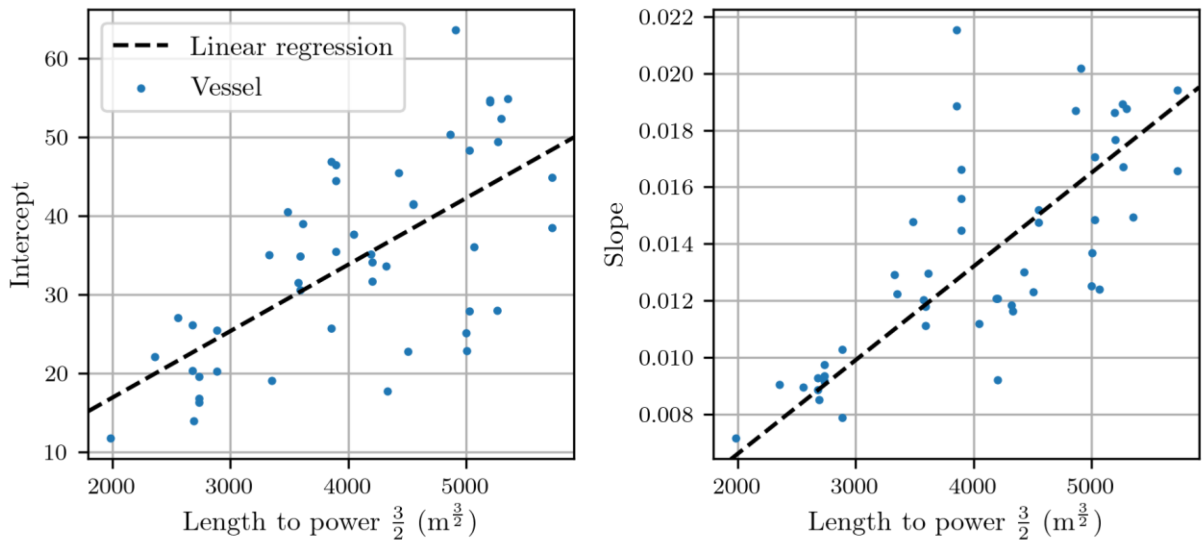

Fig.1: Parameters a_i (intercept) and b_i (slope) estimated from Eqs.(5) and plotted against vessel length to the power $k = \frac{3}{2}$ for a sample of $N = 98$ cruise vessels.

In Fig.2 we have presented LOWESS plots of the model residuals. We note that apart from a couple of vessels, the residuals as a function speed through water seem reasonably balanced. Moreover, there seems to be no obvious dependence on vessel length in the average residual data.

Note that even though we have used measurement data with 15-minute frequency in this example, the model could equally well be fitted using low frequency data (e.g., noon reports). In this case we can eliminate aggregation error by combining the low frequency fuel flow data with high frequency inputs like SOG and sea current forecasts as was done in *Antola et al. 2017* and *Schmode et al 2020*. This might be necessary when building models for many non-cruise vessel types (such as tankers, bulkers, cargo vessels and the like) where dedicated fuel flow meters have been installed less often.

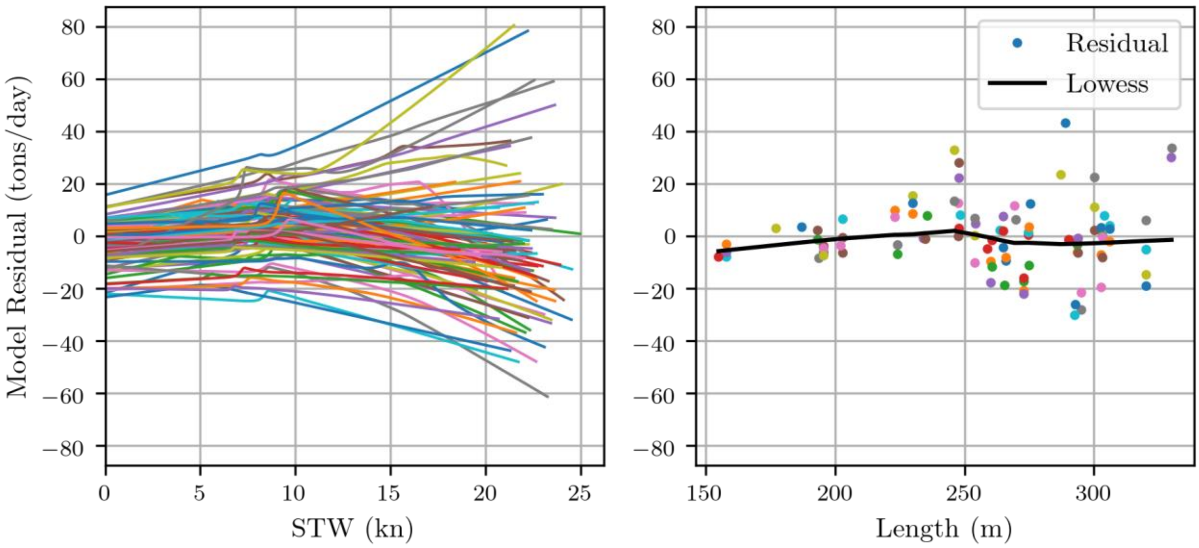

Fig.2: Left: LOWESS plots of the model residuals as a function of speed through water for each of the N=98 vessels. Right: The average model residual for each vessel as a function of vessel length.

2.3. Characteristics vs effects

In our study, we begin by dividing our set of *N=98* cruise vessels into two samples: a training sample and a test sample, each consisting of 49 vessels. Using the 15-minute frequency data we then fit several models that include a different number of terms to model the external effects and a different number of vessel characteristics. Every one of these models includes at least a term for the speed through water cubed and an intercept to model the service power consumption similarly to the simple model in Section 2.2. However, we also add additional terms one-by-one, to account for engine idle consumption, wind resistance, stabilizer resistance, wave resistance and squat effect. Similarly, one-by-one we add additional characteristics that the model parameters depend on. For the characteristics we use vessel length, deadweight tonnage, breadth, and the days since last drydock, however, we apply simple transformations and scaling for each of the variables to reduce intercorrelation. We then compare the performance of these various models against each other.

Table I: The RMSE values (tons per day) for different data free models evaluated on the test data. The number external effects included in the model increases when going to the right and the number of vessel characteristics included in the model increases when going down. More precisely, each column corresponds to a model that includes a term for the effect in that column plus terms for every effect in the columns to the left plus an intercept term. Each row corresponds to a model that includes a dependency on the characteristic in that row plus dependencies for all characteristics in all the rows above.

	Speed through water	**Engine idle consumption**	**Wind resistance**	**Stabilizers**	**Wave resistance**	**Squat**
Length	18.79	16.63	15.77	15.74	16.02	15.96
Deadweight tonnage	17.60	15.21	14.16	13.41	13.44	13.47
Days since drydock	17.04	14.72	13.67	13.06	13.19	13.22
Breadth	17.40	15.37	14.38	13.87	14.07	14.10

The root mean square error (RMSE) values evaluated from the test data for the obtained ensemble of different models are presented in Table I. We note that generally speaking, the values decrease both when moving down and moving to the right. In other words, the model becomes increasingly more accurate the more effects and the more vessel characteristics we include in it.

In general, significant improvements to the data free model's accuracy are hard to achieve, and already a simple model can predict the actual fuel consumption reasonably well.

2.4. Estimating prediction accuracy for a full model

The evaluation of the model's accuracy, considering all six effects and four characteristics from Table 1, is conducted using test data. When comparing the modeled data to the actual measurements, the RMSE in fuel flow for vessels sailing at speeds over 5 knots was determined to be 14%. The measurement vs. model prediction and relative model residuals are presented in Fig.3.

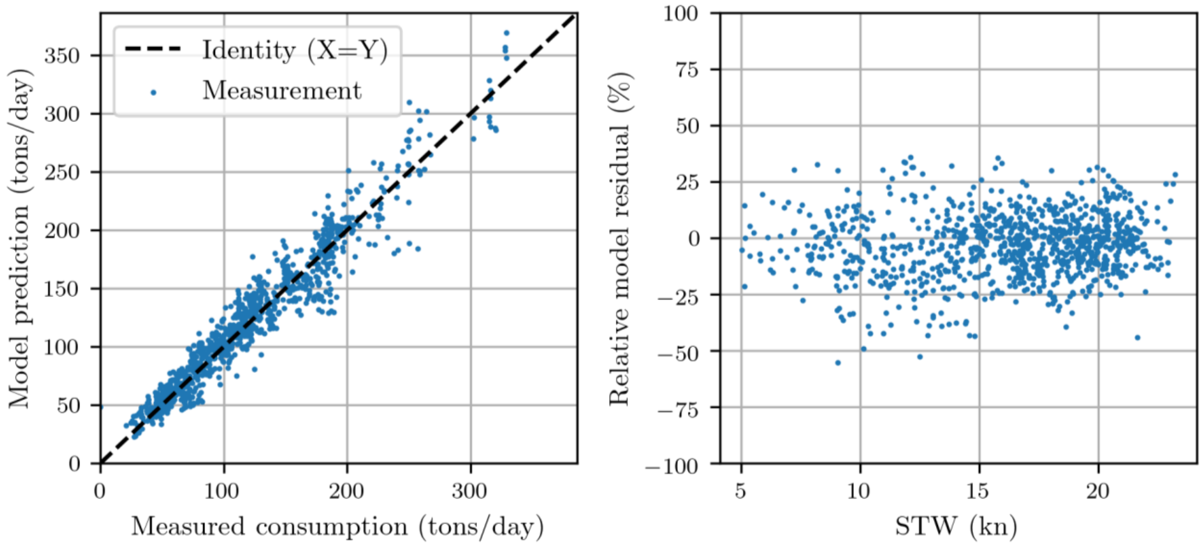

Fig.3: Left: Measured vs modeled consumption of 1000 randomly sampled data points with STW over 5 kn from test data set. Right: Relative residual of fuel consumption as a function of vessel speed.

3. Applications

Data-free models have many applications, ranging from optimization and verification to predictive analysis etc. These models enable evaluation of alternative routes, the estimation of fuel consumption for different vessel configurations, and the comparison of performance across multiple vessels. In this section we present two different applications for the data free model introduced in Section 2.

3.1. Leg performance analysis

Data-free models provide the means to optimize and analyze leg performance, enabling speed optimization at various stages of the voyage, including planning, execution, or post-voyage. Fig.4 presents an example where an actual speed profile from a 6200 nautical mile route was obtained, and its corresponding fuel flow rate was simulated. The simulation resulted in a fuel mass estimate of 1558 tons for the route. Subsequently, the same model was employed to optimize the voyage, resulting in a simulated fuel mass of 1515 tons after optimization, representing a fuel savings of 3%.

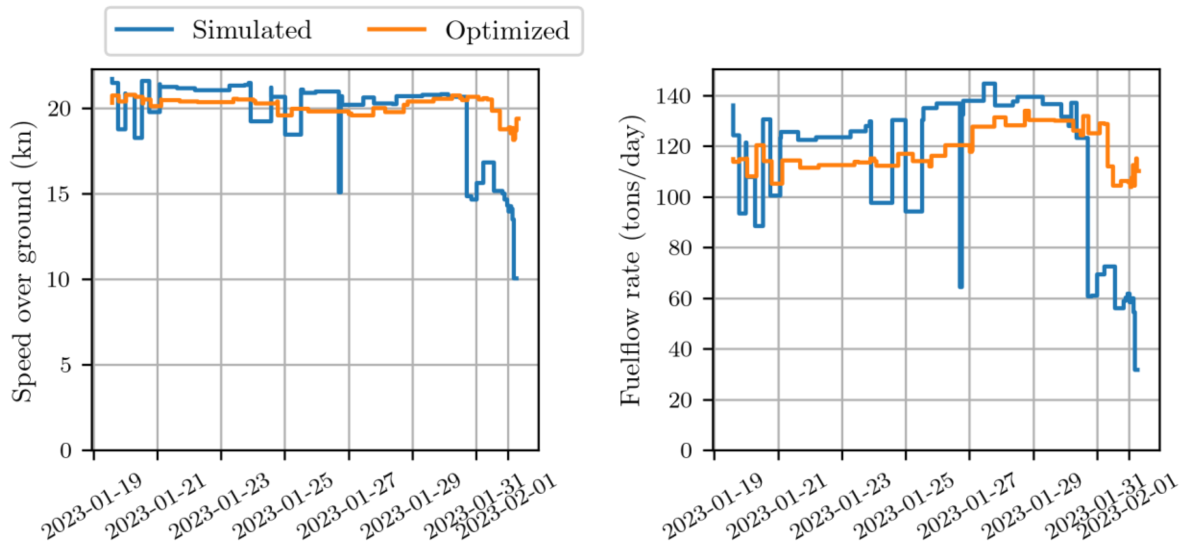

Fig.4: Simulated and optimized fuel flow rate

3.2. Fleet emissions estimation

To estimate fleet emissions, EU MRV data was utilized. Specifically, emission data and AIS tracks from 2021 were acquired for 107 passenger ships. Among these vessels, 20 were identified as exclusively sailing in Europe, thereby providing comprehensive MRV reports for the entire year. The modeled CO_2 emissions were calculated through a three-step process. Firstly, AIS tracks with a 1-hour resolution were downloaded for each vessel. Secondly, weather data for each point in the AIS tracks was obtained from a database. Lastly, vessel characteristics for each ship were downloaded from Clarkson. By combining the data gathered in steps 1-3, the fuel flow and CO_2 emissions of the vessels were simulated for the year 2021. The results of this simulation are presented in Fig.5. Notably, the figure clearly demonstrates an overestimation of CO_2 emissions by the model, which can likely be attributed to discrepancies in the vessel's fuel consumption during port periods. This can be for example due to difference in the amount of service power consumption in the ships that are sailing only in Europe.

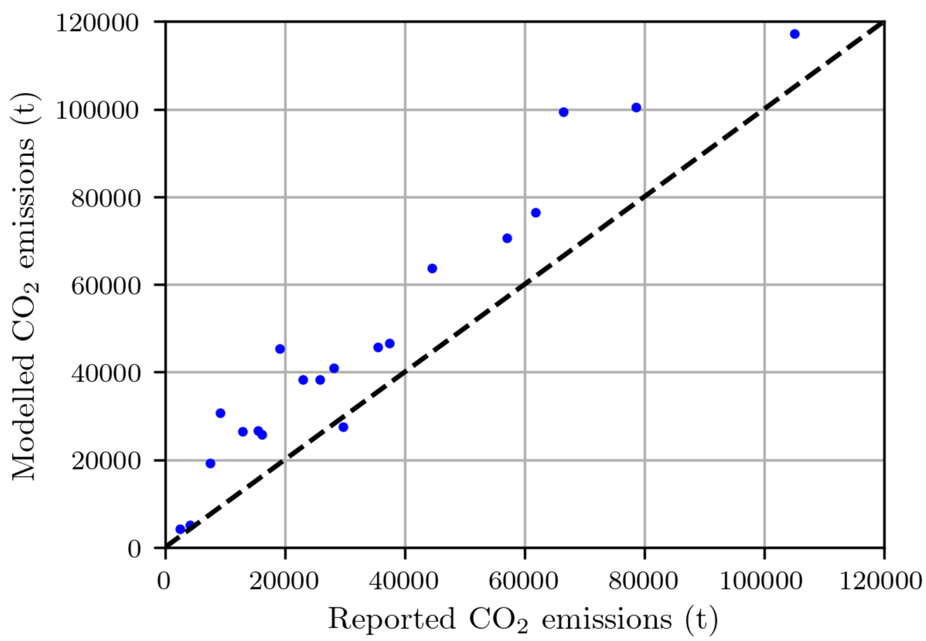

Fig.5: Reported vs. simulated CO_2 –emissions for year 2021 for 20 vessels.

4. Discussion

In this paper we have presented a simple hierarchical vessel fuel consumption model fitted on high frequency data collected from cruise vessels. Compared to the Bayesian hierarchical model in *Solonen at al. (2021)* the model presented in this paper is easier to fit and takes into account more of the vessel's characteristics. Based on our analysis it also gives reasonably accurate predictions. However, our model does not fit into the Bayesian framework and without additional safeguards, might result in unphysical model parameters in some extreme cases.

We note that cruise vessels are in general hard to model without dedicated fuel flow measurements. This is because a significant amount of the total fuel consumption is related to service power consumption, which can differ a lot from vessel to vessel and is driven also by many factors that are unmeasurable in practice, and because hull fouling is expected to have bigger effect for cruise vessels that spend relatively long time periods at port compared to many other vessel types. Fitting a similar type of model for other types of vessels might therefore yield even more accurate results.

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Data Recording on Board – Are We Getting it Wrong from the Start?

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Abstract

This paper discusses data acquisition strategies in performance monitoring, moving beyond the black-and-white discussion on manual vs automatic recording. The benefits and drawbacks of both approaches are shortly recapitulated, before presenting a mixed strategy for high data quality at reasonable effort. Using high frequency sensor data only where required and improving the noon report data quality for everything else, is often a more sustainable approach to vessel performance management than trying to replace all manual data entries with sensors.

1. Introduction

Increasing fuel costs and stricter regulations on CO_2 emissions push the shipping industry to take a closer look on vessel efficiency. More and more companies invest in professional solutions to measure performance parameters on board, process and evaluate them, and implement the results in their decision-making processes.

Good quality results rely on good quality data evaluation methods, which in turn require good quality raw data from the vessels, Fig.1.

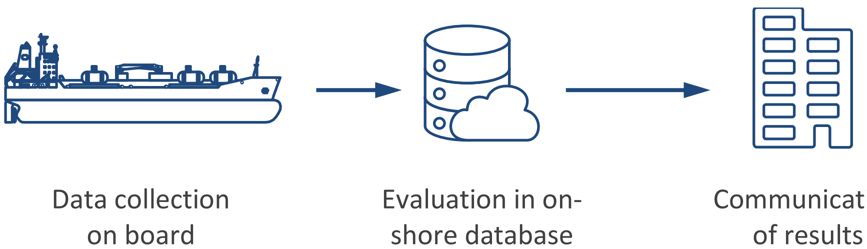

Fig.1: Typical information chain for vessel performance monitoring

However, while the data processing algorithms using advanced statistical methods, machine learning or other suitable solutions is widely discussed and promoted by the analysis service providers, the collecting of raw data on the vessels themselves is often overlooked. Much of the quality of the essential information is actually defined long before the first dataset is recorded. The designing of an adequate data acquisition solution is an important additional first step to reach reliable results at the end of the information chain, Fig.2.

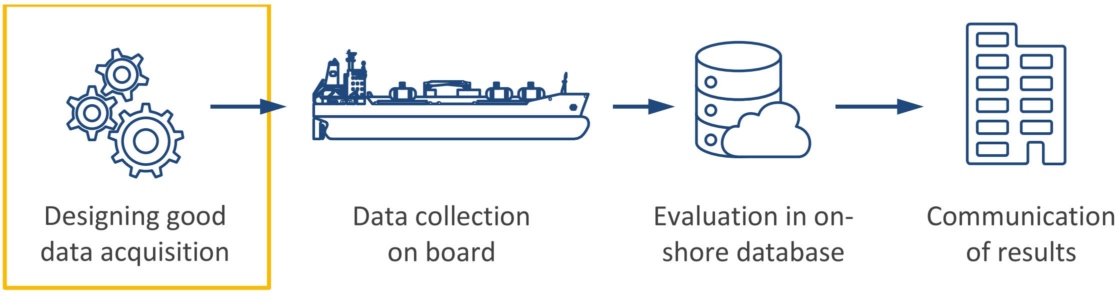

Fig.2: Information chain with added data acquisition planning

This paper looks at different data collecting methods and puts them in perspective with the most relevant questions the data are eventually supposed to answer.

2. High Frequency Sensor Data vs. Noon Reports

The mandatory submission and verification of vessel consumption data by the IMO DCS and EU MRV processes has made the shipping industry more aware of inconsistent or inaccurate fuel recordings. Tank soundings and manual reporting processes are often considered inadequate for the future demands of ship modelling. Studies have shown an inherent uncertainty in noon report data [(1)] and many shipping companies consider switching to automatic sensors as their primary source of vessel consumption information.

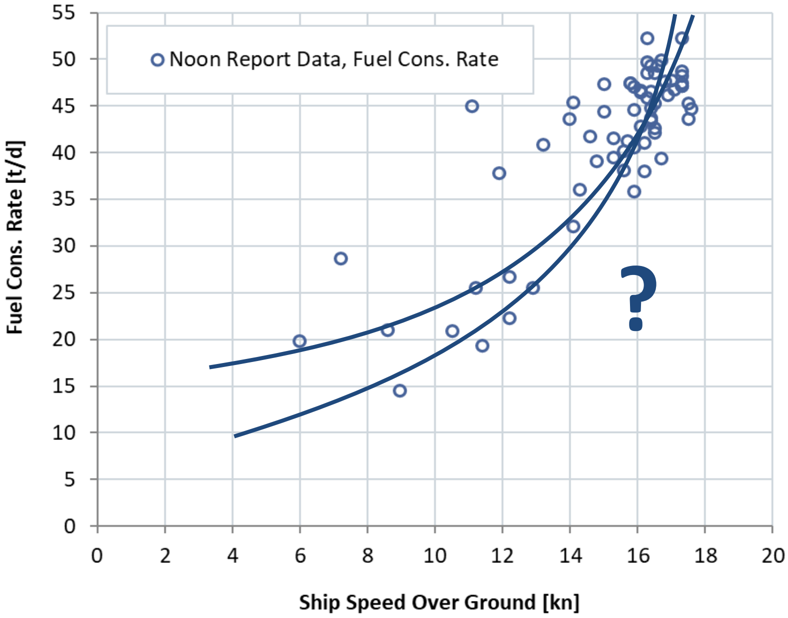

Fig.3: Speed and consumption data from noon reports, exemplary three-month period

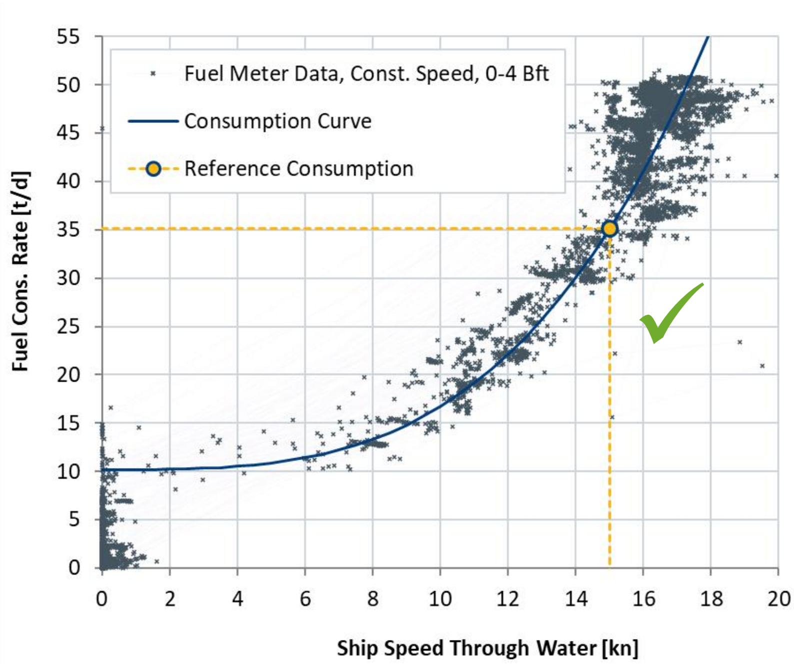

Fig.4: Speed and consumption data from sensors, 10 minutes intervals, same three-month period

In addition to working without manual entering of numbers in a form, automatic sensors also have the benefit of delivering readings in almost any desired frequency, e.g., 1 minute or 10 minutes intervals instead of just one speed and consumption entry per day in a traditional noon report. The graphs shown in Fig.3 and Fig.4 illustrate the difference, using a vessel consumption curve as an example.

It becomes obvious that the data in the noon reports are not sufficient to derive a consumption curve reliably, Fig.3. The majority of data points cluster at the operation speed of the vessel and the scatter of data at slower speeds is large. The sensor-based diagram on the other hand makes it very easy to determine the shape and position of an approximation curve, Fig.4, so that data points taken at various speeds can easily be normalized to a defined reference speed (15 kn in this example). In addition, when ambient conditions are also available for each point, the higher measuring frequency significantly enhances the informational content of the data and makes them accessible to further analytics and advanced statistical methods. For this purpose, the sensor data have some obvious benefits.

3. Equipping a Vessel for Automatic IMO DCS Data Collection

Regarding at the requirements for IMO DCS and EU MRV reporting, though, main engine (abbreviated M/E hereafter) consumption and ship speed are not the only necessary inputs. In order to collect all data with automatic sensors, all consumers must be equipped accordingly. Including an additional shaft power meter and a wind anemometer for further analytics, the sensory equipment layout of the vessel could look something like the example shown in Fig.5.

The measuring devices are connected to signal converters which feed their data to the ship's Ethernet system and the subsequent IT infrastructure on board. On a cargo vessel with vibrations from the M/E, each cable, coupling, and the devices themselves are potential points of failure.

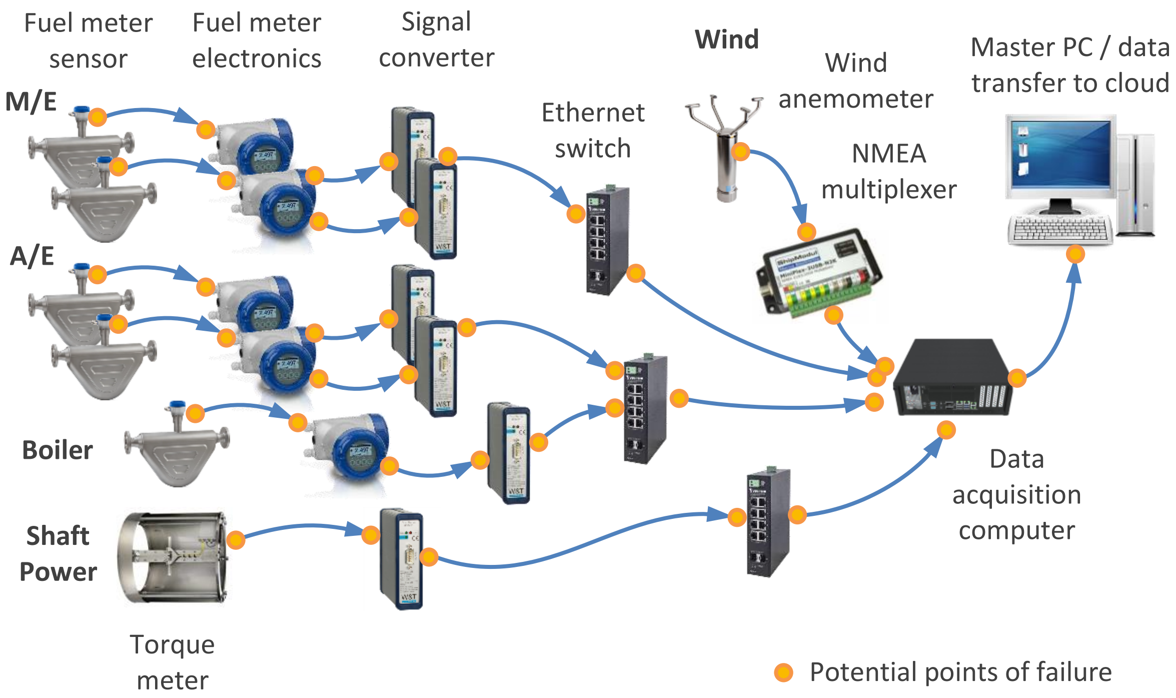

Fig.5: Multiple electronic devices and connections create a large number of potential points of failure

If one of the signals fails, this is usually detected by automatic data checking processes down the line. Finding the technical reason for the error, though, can be a challenge. Firewall settings, IT system updates, hardware issues, etc., can all be the potential culprits. Ship crews understandably often lack the experience to identify the problem reliably and quickly. Assistance from experts at the office by remote access may be time consuming as well. Consequently, and especially when new hardware is needed, it can take several days, weeks or even months until the complete system is fully restored.

Missing data for a limited period of time are no big issue for evaluations like hull condition monitoring. Hydrodynamic analyses require the ship to be moving, so while it is in port or on anchorage, there is a gap in the useable data anyways. The evaluation will just be resumed as soon as the vessel is back in service.

For calculating the Annual Emission Ratio (AER) and CII rating, though, missing data are a problem. A total, yearly sum of CO_2 emissions cannot be calculated if some of the fuel consumption data is missing. So, when that happens, the responsible companies have to resort to noon reports as a backup. This implies that even when sensors have been installed, these documents still need to carry all the required information, if only as a redundancy. Furthermore, present and future correction factors in the CII guidelines require to not only record the amount and type of fuel that was consumed, but also the purpose for which it was used, *IMO (2022)*. This added differentiation is difficult to realize with sensors. Consequently, manual entries in noon reports will still be a relevant source of information for many years to come.

4. Designing an Efficient Data Acquisition to Meet the Requirements

As the previous chapters already suggest, vessel efficiency evaluations and the IMO / MRV data collection schemes have some very different requirements regarding the data acquisition. This becomes even more evident when comparing the two purposes systematically, Table I.

Table I: Requirements of data acquisition for hull condition monitoring and IMO DCS / EU MRV

	Hull Condition Monitoring	IMO DCS / EU MRV
Required data	Ship speed through water, Propulsion power and/or M/E fuel consumption rate, Wind conditions, Ship speed over ground, Vessel draft, Further vessel and ambient conditions like trim, swell, water temperature and depth, rudder angle, etc.	Distance run, M/E fuel consumption, A/E fuel consumption, Boiler fuel consumption, Other fuel consumption, Fuel types used, (Purpose of fuel use, if applicable)
Required recording frequency	Preferably 1/h or higher	Per voyage
Required continuity	Moderate importance, interruptions lead to a temporary lack of evaluation	Crucial, interruptions lead to incomplete yearly sums

There is almost no overlap between the two columns, neither regarding the recorded parameters nor in the required frequency or the implications of temporary data gaps. The only data that have a direct accordance are the speed over ground (abbreviated SOG hereafter) / distance run and the M/E fuel consumption rate in case it is used to reference the propulsion power for hull condition monitoring.

Since the M/E is also the largest fuel consumer on cargo vessels, this is where the investment in measuring devices also makes the most sense financially. Monitoring the primary parameters vessel speed and propulsion energy both accurately and in a higher frequency is beneficial for multiple purposes. Professional hull condition monitoring allows to react quicker and take better informed decisions, helping to keep the vessels in good condition, reducing fuel costs and emissions, but also avoiding pre-emptive hull cleanings that might wear the hull coating down for no good reason.

Understanding the vessel propulsion properly and improving the vessel efficiency has a short return on investment. Adding further sensors merely for the sake of automizing the IMO DCS data acquisition process does not have a comparable savings potential. The amount of fuel that can be reduced by optimizing the use of generators and boilers is typically small compared the effects from optimizing propulsion. This leads to a situation of diminishing returns as shown in Fig.6.

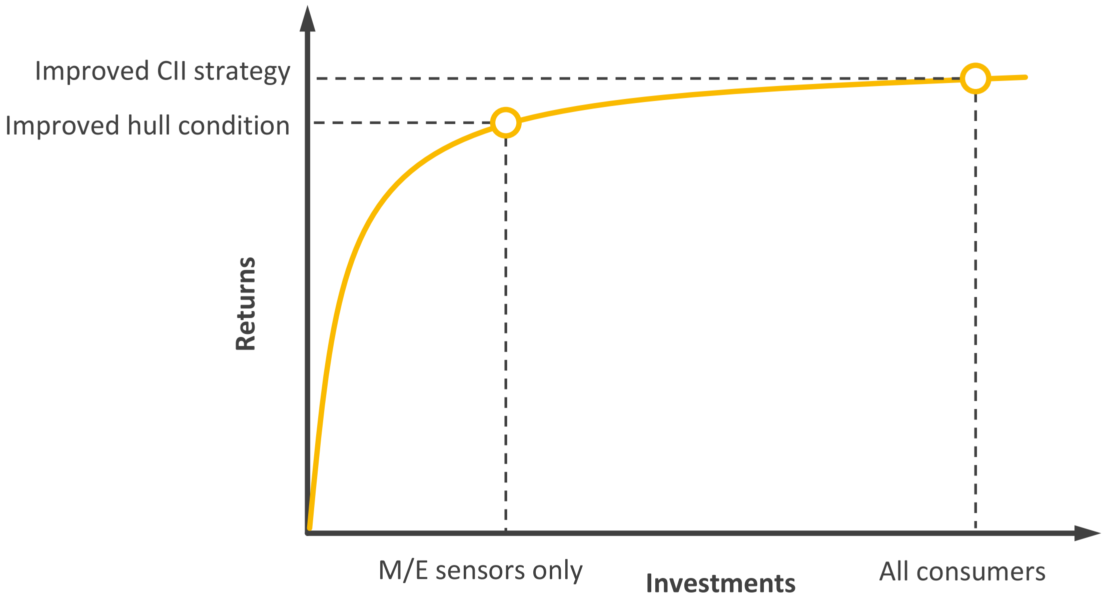

Fig.6: Diminishing returns of adding further sensors

In addition, the plausibility checks and other methods used to verify the incoming sensor data can also be applied to noon report inputs. One reason for the data uncertainty found in the 2013 study, *Aldous et al. (2013)*, certainly is that people are more careless when they feel that the values they fill in are not really used for anything important anyways. Based on the experiences of Albis Marine Performance, the quality of manual entries can be improved significantly if the crews also receive the vessel performance results as feedback.

5. Measuring Propulsion Energy and Speed Through Water Accurately

Delivered power to the propeller and ship speed through water (abbreviated STW hereafter) are the two primary parameters in ISO 19030, Measurement of changes in hull and propeller performance, *ISO (2016)*. Along with SOG and wind conditions, they are the two variables that are most important to be recorded accurately and in a sufficiently high frequency.

5.1. Delivered Power vs. M/E Fuel Consumption Rate

Torque meters are typically used to measure the shaft power of vessels. The manufacturers of the devices often specify that a zero setting or recalibration should be conducted every 6 months, https://www.danelec.com/products/ship-performance-monitoring/kyma-shaft-power-meter/. However, even when this is not done, the output data are often taken at face value. Experiences with different power meters and measuring principles have shown that some types have a significant lack of accuracy particularly in slow steaming conditions when the M/E load is comparatively low, e.g., by systematically overstating the delivered power in this range. Cylinder pressure measurements can be used to verify torque meter readings periodically, but these are normally done at 85% MCR and would not detect implausible data at lower loads. If the primary raw data are affected by errors like this, all further calculations down the information chain are compromised. Statistical methods may return misleading results, AI methods trained with skewed data will not detect these errors either, etc.

To mitigate this, Coriolis mass flow meters can be employed. They have become more and more common on cargo vessels during the past decade, and for good reason. They have no moving parts, do not require additional bypass piping or fuel filters and are generally very reliable, based on practical experience. Furthermore, they have a unique advantage over torque meters when installed as a differential measurement in the M/E booster circulation.

In this configuration, an inlet flow meter in front of the M/E measures the fuel flow to the motor and a second outlet flow meter records the fuel flow back to the day tank. The difference of fuel mass in minus fuel mass out is the fuel mass consumed by the M/E. But this also means that every time the M/E is switched off, but the booster pumps are still feeding fuel through the circulation lines, both flow meters measure the exact same fuel flow and the difference between them should be zero. If it is not, there is something wrong with one of the devices and attention is required.

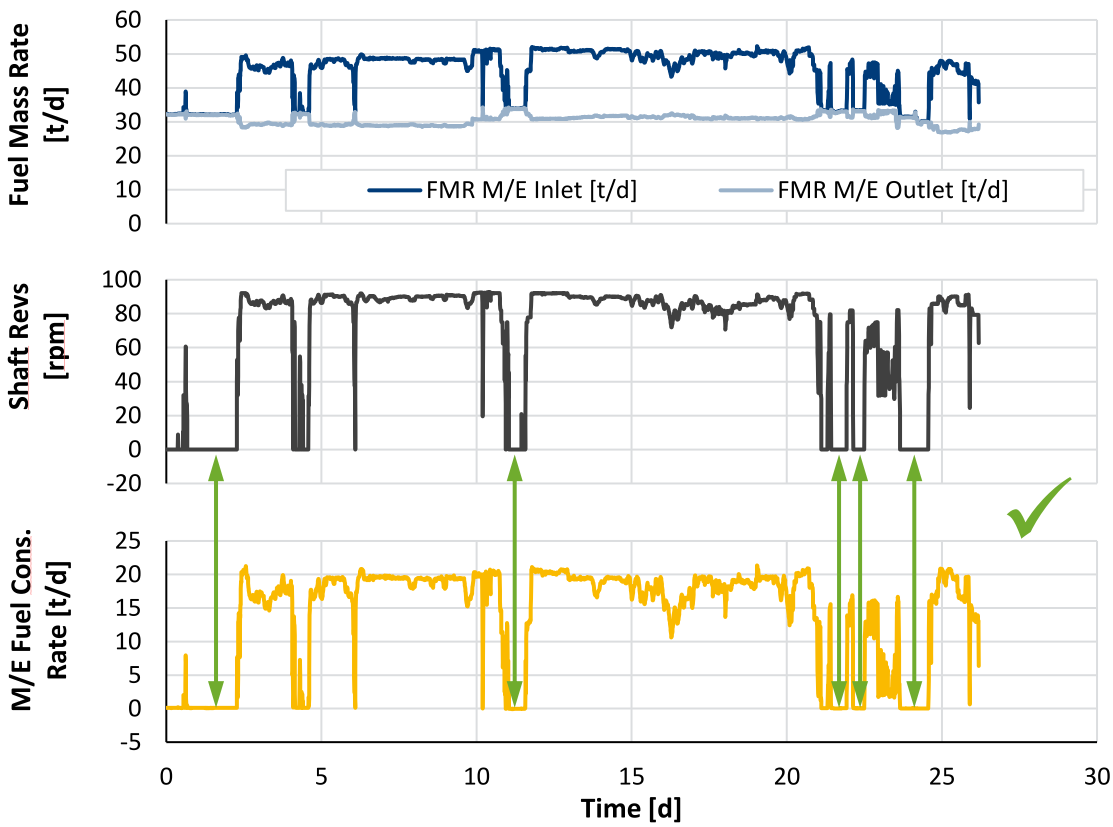

Fig.7: Exemplary vessel data showing when the correct functioning of the fuel meters can be checked

Fig.7 shows data curves as an example. Every time the vessel stops its M/E, both the inlet and the outlet flow meters still record a fuel flow (1st diagram), the shaft revolutions drop to zero when the engine is stopped (2nd diagram) and the fuel consumption rate also shows zero (3rd diagram). This is a highly valuable method to validate the fuel meter data continuously. They can then either be used to control the plausibility of the shaft power meter or to replace it entirely and provide the M/E fuel consumption rate instead of the delivered power as primary propulsion energy variable for performance evaluations.

5.2. Acquiring Accurate Speed Through Water Data

Last but not least, the STW data have a significant influence on the quality of vessel performance analyses. The power demand of a ship rises to the cube of ship speed, more or less. For instance, a power increase of e.g., 5% only speeds the vessel up by 1.5%. At 12 kn speed, that is an increase of less than 0.2 kn. As a consequence, this means that the ability to measure 12 kn STW precisely to ±0.2 kn has the same influence on the overall result as measuring the propulsion power or fuel consumption to ±5% accuracy. This basic dependency illustrates the importance of the STW variable.

But while SOG is very easy to measure highly accurately by GPS, STW is harder to tackle. Due to ocean currents, tidal effects or other types of flow, SOG and STW typically differ by 0.1 to 1 kn in most waters, but even up to 3 kn in some waters with strong currents. Two methods to determine the precise STW are widely used:

1. recording SOG and correcting it for currents using data from a weather service provider,
2. using the ship speed log on board to measure STW in high frequency.

Both methods have their benefits and drawbacks. The main benefit of using weather data to calculate a ship's STW is that all required data can be sourced on land without requiring sensors on the vessel or a data connection to it. The vessel position and SOG can be taken from the AIS signal and surface current data can be bought from weather service providers. However, there are two major drawbacks. First, the data from the weather services have a low resolution both in time and space. New data are typically available every 6h for a grid with many miles between each point. But ocean currents flow in turbulent eddies that break down into smaller eddies, which shift and move constantly. Ships can easily travel in and out of several of these eddies within a few hours, making it impossible to obtain the exact surface currents for any precise position and time from weather data. Second, the surface currents offered by weather services are mainly calculated from satellite data which only observe the surface of the water. Wind influences the currents near the surface, so that their speed and direction differ from currents deeper down in the water. On many vessels, more than 50% of the hull friction happen many meters below the surface, and satellites cannot assess the currents at that depth, Fig.8.

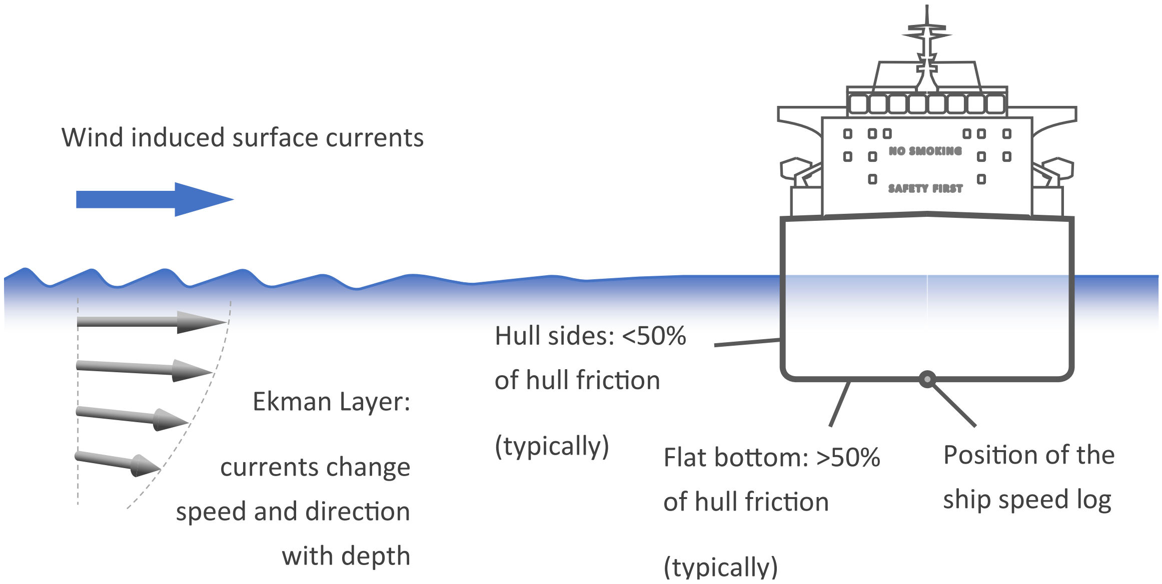

Fig.8: Measuring ship speed through water where hull friction is most relevant

The major benefit of recording the STW data from the ship speed log directly is that they are measured where most of the hull friction occurs, namely at the depth of the bottom of the vessel. On the downside, ship speed logs are known to be slightly inaccurate and subjected to fouling influences. The sensors are installed on the bottom of the ship and marine growth near the sensor may influence the fluid dynamics in that particular area enough to offset the reading by some percent. In small ranges like ±0.2 kn, this offset cannot be distinguished from an actual current just by analysing the sensor data alone. To mitigate the measuring inaccuracy, correction functions that take SOG and weather data into account can be employed. For instance, the influences of the turbulent eddies in ocean currents average out over time, which improves the accuracy of the correction function.

6. Conclusion

Shipping is a competitive business in which fuel consumption and emissions become more and more important. The IMO has embarked on a mission to reduce the net CO_2 emissions to zero by 2050 and the regulations to reach this goal are developing quickly. Consumption data that were previously entered in noon reports are measured by sensors more and more. However, more electronic equipment on board also results in more potential points of failure and data gaps lead to incomplete yearly sums in the IMO DCS documentation.

High frequency data are particularly useful for the evaluation of vessel efficiency, like e.g., hull condition monitoring. For this purpose, only the M/E needs to be equipped with sensors. As a result, investing in fewer sensors where it matters the most and improving the quality of noon reports everywhere else can be the most reasonable and cost-effective way to reach good quality analysis results and consistent inputs for IMO DCS and EU MRV.

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Hull and Propeller Performance Decomposition via an Adaptive Machine Learning Framework

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Abstract

This paper deals with a machine learning methodology for decomposing hull and propeller performance. This is facilitated by an ensemble approach predicting both propeller revolutions and shaft power under consistent simulated reference conditions. The derived performance estimates are compared to ISO 19030 and a semi-empirical framework aimed at isolating propeller performance. The case ship is a >300 m cruise vessel sailing in the Caribbean Sea. The auto-logged sensor data covers seven years with three dry-docking intervals and numerous in-water cleaning events. It is concluded that the separation of propeller performance is subject to multiple uncertainty sources and can thus not be reliably assessed. The practical relevance and potential shortcomings of the method are discussed.

1. Introduction

The adoption of the revised IMO Greenhouse Gas (GHG) strategy is a crucial milestone for adhering to the Paris Agreement, however, at the same time, it increases pressure felt by various stakeholders in the maritime industry. In addition to the volatility of fuel prices and freight rates, international regulations such as the entry into force of the Carbon Intensity Indicator (CII) or the upcoming EU Emissions Trading System (ETS) incentivize shipping companies to further streamline their operations. *IMO (2022)* attributes significant potential for reducing carbon emissions by optimizing ship operations, e.g. up to 75% can be achievable through extensive speed optimization and up to 25% through biofouling management. In this particular survey, operational saving potentials show a similar order of magnitude as ship design measures. For instance, shape optimization of the hull and superstructure may lead to a reduction in fuel consumption of up to 20%, (*IMO, 2022*). In addition, synthetic and carbon-neutral E-fuels may show issues regarding upscaling and retrofitting to existing vessels, which potentially disqualifies them as a short-term measure. Hence, IMO puts the main focus of the present decade on enhancing vessel operation for minimizing the carbon intensity of the existing world fleet.

Marine growth is plaguing the operation of ships ever since and does not only lead to higher fuel consumption due to an added frictional resistance but also to the spreading of aquatic invasive species. Therefore, after the introduction of IMO regulations on ballast water treatment, it was the next logical step to establish a joint project with a focus on biofouling and its mitigation. For this reason, the GloFouling initiative has been launched by several intergovernmental bodies, *GloFouling (2022)*. As a response, the 80th session of the Marine Environment Protection Committee (MEPC) released several recommended guidelines for in-water inspections and the quantitative assessment of fouling as well as coating conditions, *IMO (2023)*. Stressing the significance of marine growth on energy efficiency, a review from I-Tech found that 44% of the entire world fleet shows hard fouling of 10%, which in turn corresponds to a 36% increase in required propulsion power, *I-Tech (2020)*. Thus, the importance of ship performance monitoring has been amplified through the recently stipulated international regulations.

In most studies, including the industry standard ISO 19030, an *aggregated* performance indicator is provided, i.e. considering both hull and propeller. However, for predictive maintenance, i.e. proper scheduling of propeller and/or hull cleaning, the decomposition of both contributions is a prerequisite. *Carlton (2018)* postulates that the performance of the hull and propeller are of similar importance due to the decrease of the propulsive efficiency caused by biofouling, erosion due to cavitation, and other mechanical damages of the propeller blades. In fact, propellers show all fouling types seen on ship hulls, except extensive weed fouling. *Farkas et al. (2021)* underline that the propeller surface per unit area shows even greater importance on vessel performance than the hull surface. Obviously, both components are highly interrelated complicating the separation of hull and propeller performance due to inherent interaction terms. Generally, the investigations of the effect of increased propeller roughness can be split into two categories: Simulation-based and data-driven studies.

In open-water conditions, *Sezen et al. (2021)* found in a Computational Fluid Dynamics (CFD) study that an increase in propeller roughness leads to a decrease in tip vortex cavitation and thus underwater radiated noise. Regarding propeller efficiency, *Farkas et al. (2021)* examined the influence of increasing surface roughness on three benchmark propellers using CFD and in the case of heavy calcareous fouling an efficiency decrease of around 20% was reported. Based on in-service data, the cleaning effect of polishing a heavily fouled propeller (i.e. heavy slime and barnacle fouling) on a large tanker was with ca. 8% in a similar order of magnitude (personal communication M.H. Schmidt, June 2023).

In an early data-driven study, *Andersen et al. (2005)* used 2 years of noon-reported data of two sister vessels for determining a ca. 4% increase in propulsive efficiency when using a KAPPEL propeller in comparison to using a conventional propeller. Based on high-frequency sensor data, *Paereli et al. (2016)* investigate the impact of a propeller polishing as well as the retrofitting of propeller boss cap fins on the hydrodynamic performance of a tanker. The overall decomposition problem is discussed and challenges are outlined. Similarly, *Ballegooijen and Helsloot (2019)* utilize approximately 1 year of sensor data acquired aboard a passenger vessel for determining the individual components of hull and propeller performance. Both mentioned studies rely on the availability of torque and thrust measurements but still show considerable uncertainty. The only known machine learning approach for decomposing hull and propeller performance has been proposed by *Park et al. (2018).* The presented methodology builds upon an ensemble approach, where the relationships between ship speed and propeller revolutions and between propeller revolutions and shaft power are modeled by two separate estimators. Several theoretical considerations are presented using synthetic data and a forecasting model is presented, which is claimed to be capable of extrapolating vessel performance into the future.

In *Mittendorf et al. (2022a)* it was shown that ship monitoring data is subject to distributional shifts or rather *concept drift*, which results from the attachment and removal of biofouling or changes in the operational profile. Hence, vital statistical assumptions of machine learning are violated and an incremental learning paradigm is necessary for capturing these effects. The present case study – considering a larger cruise vessel – is subject to higher biofouling pressure due to its operational area and profile. Due to the twin-screw arrangement and the 6-bladed propellers, i.e. a larger wetted propeller surface susceptible to fouling, the dedicated monitoring of propeller performance seems appealing for scheduling propeller cleanings or inspections. For this reason, the approach of *Park et al. (2018)* will be implemented into the adaptive method proposed by *Mittendorf et al. (2022a).* In contrast to *Park et al. (2018)*, there will be a larger focus on actual in-service data and the comparison to other benchmark methods for checking the validity of the methodology. Similar to *Mittendorf et al. (2022a)*, the aggregated performance estimate is compared to the results of the ISO 19030 standard, whereas the isolated propeller performance will be validated against the results of a semi-empirical framework, which relies on the Wageningen B propeller series. It is stressed that the dataset does not comprise thrust measurements and therefore it is assumed that the delivered propeller thrust is unaffected by the surface roughness. In fact, this assumption can be supported by the experimental study of *Mosaad (1986)*. In the final part, individual uncertainty sources and shortcomings of this study are elaborated on.

2. Dataset

The case ship is a >300 m cruise vessel (>100,000 GT), which predominantly operates in the Caribbean Sea. In general, cruise ships are exposed to relatively high biofouling pressure due to service in areas with a higher water temperature and an operational profile dominated by frequent port calls. In fact, the present case ship shows an average activity level, i.e. instances with notable forward speed, of slightly more than 60%. The operating area is characterized by significant sun exposure, higher salinity in open sea conditions, and a higher density of nutrients and chlorophyll in coastal regions. All of the above are crucial driving factors for marine growth. In addition, *Carlton (2018)* underlines that the viscous resistance component of cruise ships makes up around 66% percent of the calm water resistance, i.e. the increased surface roughness due to biofouling has a high impact on the ship's total resistance. Other complexities of cruise vessels include the large windage area and the balconies, which severely affect the wind resistance as well as the drift of the ship in adverse weather conditions. Typically for cruise vessels, the case ship is equipped with two propellers with a fixed pitch and shaft brackets. The twin-screw arrangement leads to a relatively low wake fraction, i.e. a lower interaction of hull and propeller flow, which may benefit the decomposition of the related performance components. Moreover, cruise ships sail under similar draft conditions, eliminating the draft dependency of the performance indicator.

The present dataset encompasses 7 years of auto-logged sensor data and includes 2 dry dockings with full blasts. The considered shipping company maintains the hydrodynamic performance of the ship through numerous in-water cleanings. Additionally, silicone-based fouling release coatings (FRC) are applied to the hull in case of all three dry-docking intervals. Another interesting aspect of this dataset is the abrupt change in the operational profile (as well as biofouling) due to the restrictions imposed due to the spread of the COVID-19 pandemic in early 2020. This not only led to a decrease in activity but also in forward speed, which can be seen in Fig.1, where the distribution of the non-dimensional forward speed (*Fn*) is depicted. As can be inferred, the distribution of the advance speed is multimodal, whereby it is understood that the peak around *Fn*=0.09 only results from sailing during the COVID-19 period.

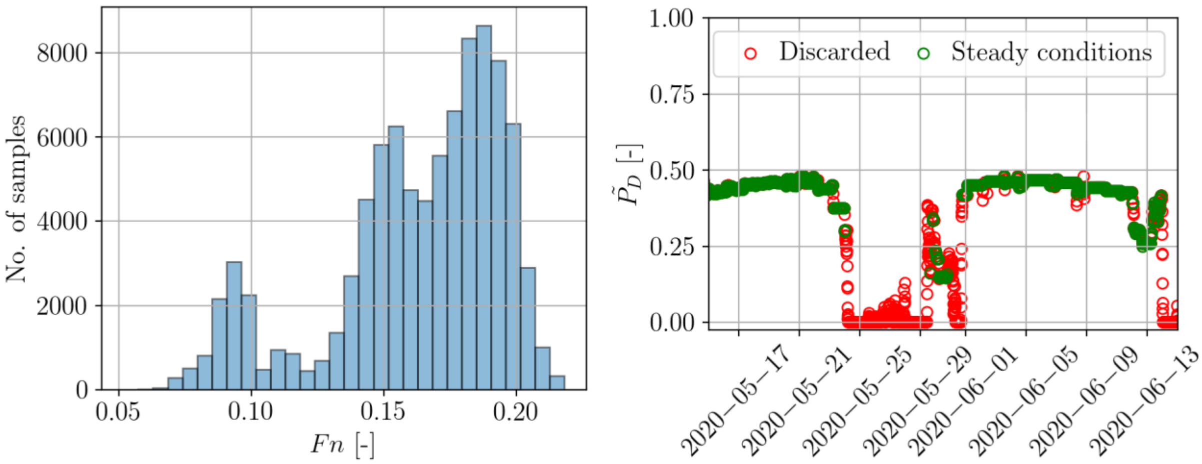

Fig.1: Histogram of the non-dimensional ship speed *Fn* based on the filtered dataset (left) and filtering for steady sailing conditions shown for the non-dimensional shaft power P_D in early 2020 (right)

The initial dataset has a sample size of approximately 6.2×10^6, but the data is resampled to 10-minute window-wise averages. Moreover, outliers and instationary samples are disregarded by a rigorous filtering methodology, with details presented in *Mittendorf et al. (2023a)*. In short, samples where GPS and log speed are below 5 kts are dropped and shallow water instances were filtered by dismissing samples with a depth Froude number Fn_H>0.5. Unsteady conditions were identified based on the relative variance of several sensor readings, e.g. heading, shaft power, etc. A sample result of the filtering procedure is shown in Fig.1 on the left-hand side. It is noted that the tilde indicates normalization – in this case by the maximum of the measured shaft power. It is appreciated that acceleration phases and port stays are filtered out by the applied procedure. Moreover, the bathymetry data and the sea surface temperature are taken from a known hindcast provider for the reason of robustness. In the present case, sea state information is not considered since the case ship has slender hull lines, i.e. is less affected by added-wave resistance, and also due to the extensive use of weather routing by the respective shipping company.

3. Methodology

In the present section, both the machine learning approach and the semi-empirical framework are elucidated. After an initial study, it was decided to provide an aggregated propeller performance score for both portside and starboard propellers. In addition, both methods provide the relative added power (or power increase) $\Delta\widetilde{P}_D$ as a key performance indicator (KPI), which is defined in the following.

$$\Delta\tilde{P}_D = \frac{P_{D,t} - P_{D,t_0}}{P_{D,t_0}}$$

The indexes t and t_0 denote the running time index and the baseline (or origin), respectively. In order to keep consistency with the work of *Park et al. (2018)* the power increase was chosen over the speed deviation, which is seen as the default KPI in the ISO 19030 standard. In addition, it is emphasized that both methods rely on the assumption that the propeller thrust is not a function of the surface roughness.

3.1. Machine learning approach

Incremental learning pertains to the field of continual learning, which comprises several advanced learning paradigms mimicking the sequential way of human learning. In fact, adaptability is a key characteristic of a digital twin according to *Kritzinger et al. (2019)*: (1) A digital model can be seen as a simulation model, e.g. CFD, since there is no feedback from the actual physical asset. (2) A digital shadow has a one-way data flow to the physical asset, e.g. a static machine learning model, (3) whereas a digital twin has a two-way data flow, i.e. the model is continuously updated and deployed to the physical object. Thus, the presented adaptive methodology can be considered a digital twin.

The underlying regression model is a multilayer perceptron consisting of 4 hidden layers. The considered features include speed through water *STW*, draft T, trim ΔT, sea surface temperature *SST*, and the vector components of the relative wind ($V_{r,x}$ and $V_{r,y}$). As mentioned, no baseline data is available and therefore the model has to derive a baseline from in-service data obtained during the first 3 months considered. The so-called warm-up period is used for training the entire network, whereas at times after only the parameters of the last two layers were adapted based on a subsample taken from the time interval. Following the findings of *Mittendorf et al (2023b),* layer freezing is applied for maintaining the knowledge of prior training instances. Moreover, the training methodology is conducted window-wise, i.e. a 3-month window is shifted roughly every month (i.e. 40 days). It is noted that this leads to a smoothing effect but may also introduce a lagging behavior of the performance estimate. The calculations were performed on an Intel Core i7-8565U CPU, 1.80GHz with 16 GB physical memory (RAM), and the used deep learning library is TensorFlow 2.6, *Abadi et al. (2015)*.

In contrast to other papers, the degree of concept drift (or biofouling) is determined implicitly. The individual performance contributions are assessed under the same simulated reference conditions for maintaining consistency. The enforced conditions roughly reflect sea trial conditions, i.e. a moderate seaway with 5 m/s headwind. Additionally, the mean of the advance speed, draft, and trim are considered. According to *Park et al. (2018),* it is assumed that hull fouling leads to speed reduction at constant propeller rpm, which is caused by an increase in frictional resistance. In other words, hull fouling results under constant speed in an rpm increase due to the required thrust increase. The propeller fouling component on the other hand leads at constant propeller rpm to a torque (and thus power) increase. Trivially, the total ship performance is the sum of these two subcomponents. This is illustrated in Fig.2, where two rpm-power curves are shown for both baseline and actual conditions. The ensemble approach is carried out in a sequential manner. Initially, for a given ship speed, the rpm for baseline (rpm_0) and actual conditions (rpm_1) are determined, where the latter is taken from the adaptive model. In the second step, the required engine power at points a, b, and c in Fig.2 are calculated based on the previously obtained rpm values. For this reason, a separate model is needed, which maps the relationship between propeller revolutions and required shaft power for different environmental and operational conditions. This presented sequential approach has the disadvantages of being computationally less efficient and the possible propagation of errors.

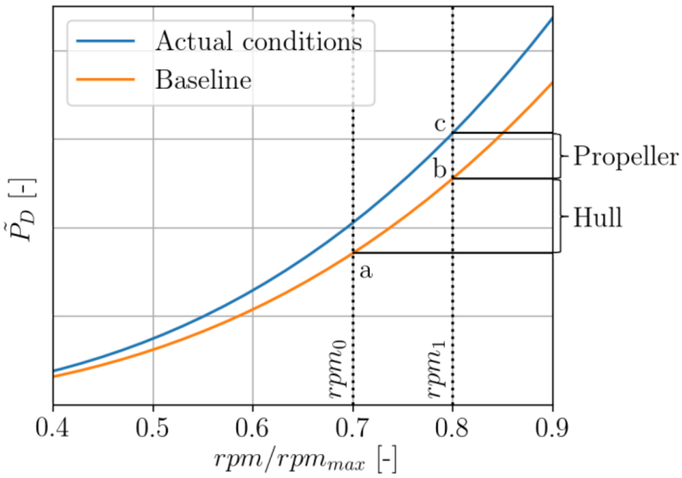

Fig.2: Contribution of hull and propeller performance for two different conditions considering shaft rpm vs. shaft power, according to *Park et al. (2018)*

3.2 Semi-empirical approach

The presented data-driven approaches in the literature review in Sec. 1 rely on thrust measurements. However, these can be unreliable, as shown by *Hansen (2012)* using data from a Post-Panamax container vessel. Additionally, thrust meters are rarely installed onboard vessels – including the considered case ship. Interestingly, *Paereli et al. (2016)* outline a methodology for isolating propeller performance without the need for thrust meters, and the following method points in a similar direction.

Due to the lack of sea trial and propeller curves, a semi-empirical framework is set up. The case ship is a twin-screw vessel and is equipped with two fixed-pitch propellers (FPP) with a blade number of Z=6. The diameter D is known, but the open-water propeller curves are unavailable. The calm water resistance is calculated following the procedure presented in *Hollenbach (1998)*, a 20% sea margin is applied, and the approximate propeller is optimized for a design speed of 22.5 kts. The propulsive coefficients are calculated according to Heckscher, cf. *Bertram and Schneekluth (1998)*, and the propeller curves are determined from the polynomials of the Wageningen B series, *Oosterveld and van Oossanen (1975)*. The open-water propeller curves of the obtained propeller design are shown in Fig.3 together with its geometric parameters in the caption. For the extrapolation to full scale, the Reynolds number correction presented in the ITTC'78 performance prediction method is applied, *ITTC (2017)*.

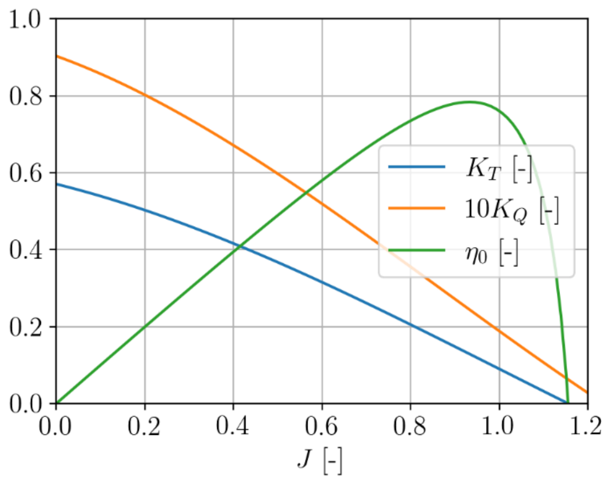

Fig.3: Full-scale open-water propeller curves according to the Wageningen B series for an FPP with D=5.8m, A_E/A_0=1.05, P/D=1.1 and Z=6. A_E/A_0 is the expanded blade area ratio and P/D the pitch diameter ratio. Only public-domain information about the vessel was used.

In Fig.3, J is the advance ratio, η_0 is the open-water propeller efficiency, K_T is the thrust coefficient and K_Q is the torque coefficient. For the sake of clarity, T is the propeller thrust and Q is the propeller torque.

$$K_Q = \frac{Q}{\rho n^2 D^5} \qquad K_T = \frac{T}{\rho n^2 D^4} \qquad \eta_0 = \frac{K_T\, J}{K_Q\, 2\pi} \qquad J = \frac{U(1-w)}{n\, D}$$

In the above equations, ρ denotes the water density, n indicates the propeller revolutions in Hz, whereas U is the ship speed and w the wake fraction coefficient. In particular, the latter two quantities are of great uncertainty. In the present context, w is calculated following *Heckscher*, cf. *Bertram and Schneekluth (1998)* and *STW* is taken as the ship reference speed. Even though the data quality of speed logs can be questionable, as shown by *Ikonomakis et al. (2021).* The starting point of the methodology is to determine J based on *STW* and the measured propeller revolutions. Afterward, the theoretical (or baseline) K_Q can be interpolated from the propeller curves (cf. Fig.3), and the baseline power is obtained through $P_D=2\pi nQ$. Lastly, the power increase can be calculated when using the measured shaft power.

The presented methodology can only provide indicative results caused by the underlying assumptions and the approximate propeller curves in particular. Furthermore, it is assumed herein that the wake fraction coefficient is constant, which may be satisfactory in the early design stages, for which the *Heckscher* formulae were developed. In actual ship operation, however, it is important to stress that w is a function of several quantities, such as speed, draft, and environmental parameters. Hence, the same filtering procedure recommended in ISO 19030 is applied in this context. Moreover, only instances in the proximity of the design speed, i.e. in the range of ±3 kts from mean speed are considered. Additional uncertainties include the full-scale extrapolation of the propeller curves and the impact of hull roughness on the wake fraction.

4. Results and discussion

In this section, the obtained results will be presented and discussed. Initially, the aggregated as well as the hull performance indicator obtained by machine learning are shown in comparison with ISO 19030 estimates. *Schmode et al. (2018)* point out several drawbacks of this standard, e.g. the draconian weather threshold. Secondly, the isolated propeller performance will be addressed, and the machine learning results are shown in parallel with the estimates from the proposed semi-empirical framework. In the final part, several uncertainty sources and limitations of this work are presented.

4.1. Hull performance evaluation

In Fig.4, the result of the ISO 19030 analysis is shown with the power increase as KPI, and the sea surface temperature is shown as a color code as a proxy variable for the biofouling potential.

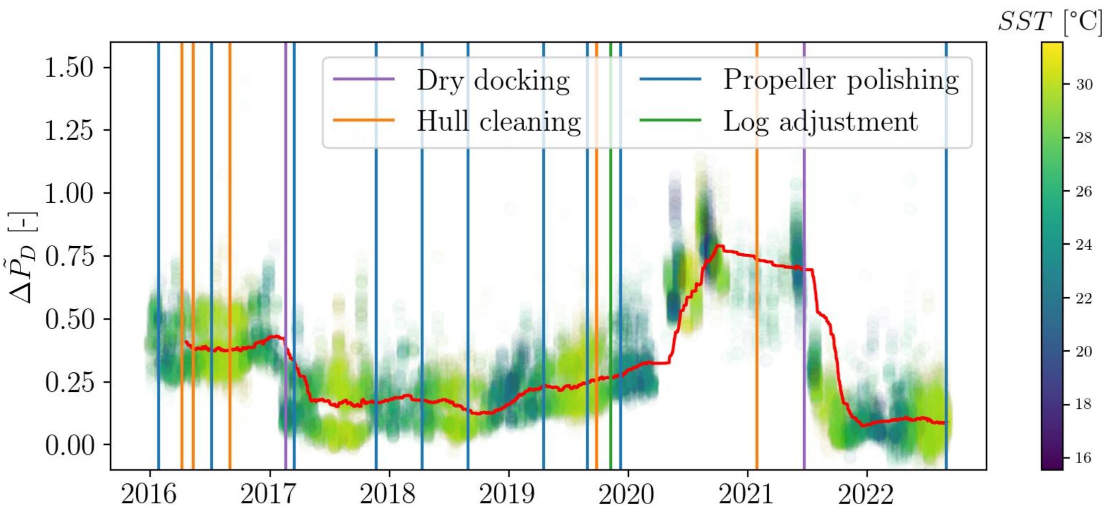

Fig.4: Power increase according to the ISO 19030 procedure with sea surface temperature (*SST*) in the colorbar and a 30-day rolling mean in red

For the determination of the required speed-power baseline for the ISO analysis, the method according to *Hollenbach (1998)* and the open-water propeller curves shown in Fig.3 are utilized. Numerous cleaning events are indicated by vertical lines in Fig.4, but only the 2 dry dockings (with full blast) lead to a notable cleaning effect considering the monthly rolling mean. In addition, the sudden shift in operational profile due to the COVID-19 lockdown and the subsequent idling (and thus increased attachment of fouling) is appreciated. In fact, the performance deterioration is somewhat exaggerated due to the change in the speed profile, which complicates the assessment of performance for the entire timespan. For these reasons, the reliability of the performance estimates is reduced during the COVID period. Overall, the individual FRC lead to relatively stable performance plateaus, except after the end of 2018, where a minor gradient in the power increase can be seen. Obviously, this may not only be a result of biofouling but also sensor drift. As a side note, no clear dependency of the KPI on the sea surface temperature, which acts as a proxy variable for biofouling potential, can be seen.

In Fig.5, two photographs from inspections of the ship hull are presented. It is noted that no similar images are available for the propellers and hence this type of analysis is limited to the hull performance Subsec. 4.1. On the left-hand side of Fig.5, the bulbous bow and a bow thruster are shown after entering the dry dock in Feb./Mar. 2017. The efficacy of the silicone FRC stands out, as only slime conditions can be seen, but no seaweed or calcareous fouling after a dry docking interval of more than 4.5 years. In addition, the typical mechanical damages on the bulbous bow caused by the anchor chains are visible.

Fig.5: Visual appearance of the bulbous bow in February 2017 after almost 5 years since the last dry-docking (left) and effect of the robotic in-water cleaning on a vertical wall in early 2021 (right)

On the right-hand side of Fig.5, a photo taken during the in-water robotic hull cleaning is presented showing the difference between a cleaned (right) and fouled (left) part of a vertical wall. This hull cleaning was conducted after the initial phase of COVID-19 in early 2021 and the fouling type is considered heavy slime conditions despite the prior elongated idling periods, which again underlines the performance of the applied FRC.

In the following, the machine learning-based results are compared to the ISO 19030 benchmark data. However, only a qualitative study is possible in this context, since the machine learning model uses the first 3 months as its baseline, i.e. conditions similar to the ones shown in Fig.5 (right). This leads to a consistent offset between ISO 19030 and machine learning results. Hence, both are depicted on individual axes in Fig.6. An initial observation is that the machine learning indicators are characterized by more variance than the rolling mean of the ISO analysis, which could be due to considering also severe sea states (V_w>7.9 m/s) in the training datasets. Still, in comparison to *Mittendorf et al. (2022a)*, a lower variance of the machine learning-derived KPI is observed and hence no linear regression is necessary.

Overall, the model is able to reproduce the aggregated long-term performance decay satisfactorily. Moreover, it is appreciated that hull performance takes up a major proportion of the total ship performance, which is expected due to the larger wetted surface area. Nevertheless, the propellers or other niche areas, such as rudders, gratings, etc., have their relevance when maintaining the hydrodynamic performance of a vessel. The ratio of hull and propeller performance appears physically plausible and is also in rough (qualitative) agreement with the results presented by *Park et al. (2018)*, even though it is a different case study. The machine learning method provides performance estimates in a 40-day interval but requires a subset length of 1000 samples, and hence no estimates can be provided during the COVID-19 period. The change in operational profile, the increased attachment of fouling, and the lower data availability increase uncertainty and impede drawing any firm conclusions in this time period. The speed log adjustment in late 2019 has apparently had no effect on the KPI, but peculiarly the propeller component seems to be larger after the log adjustment.

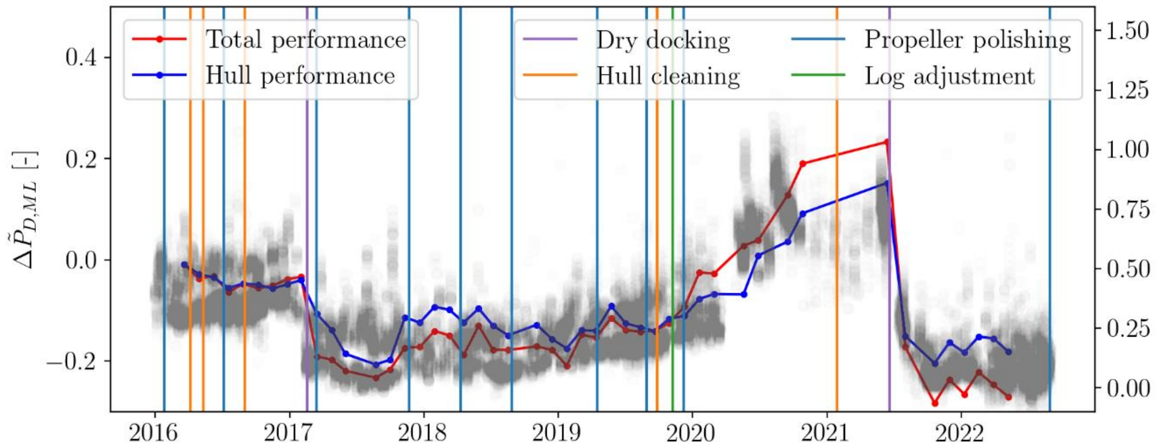

Fig.6: Comparison of the model estimates of the power increase (primary axis) to ISO 19030 results in transparent grey color (secondary axis)

4.2. Propeller performance evaluation

Similar to the previous subsection, the results of the semi-empirical method are initially shown in isolation and are afterward compared to the machine learning results. In contrast to the hull, no photographs of the propellers made during inspections are available. In Fig.7, the relative added power based on the semi-empirical framework is shown and it is noted that a bias correction was applied. As an initial observation, the propeller fouling has a seasonality and depends on the sea surface temperature. As opposed to ISO 19030, temperature-dependent seawater properties were used in the semi-empirical framework. In Fig.7, samples with *STW*>5kts are considered and a peculiar and unphysical performance increase is visible in the COVID-19 period, which is caused by the assumption of a speed-independent wake fraction coefficient and the decrease in service speed in that period.

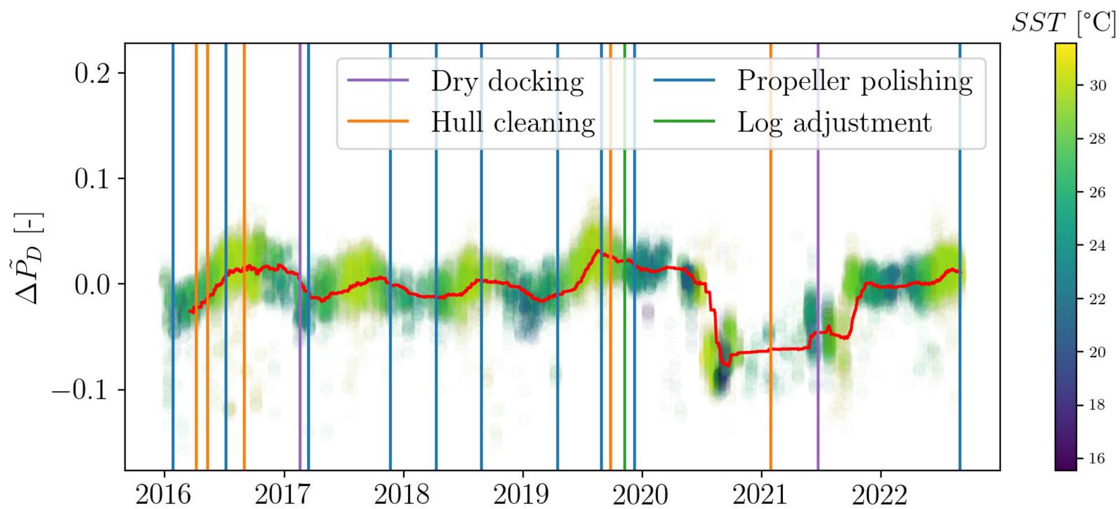

Fig.7: Result of semi-empirical framework including the sea surface temperature in the colorbar and a 30-day rolling mean in red. It is noted that no filtering thresholds are applied to the forward speed.

The seasonality of the KPI could be a result of fluctuations in the bias of the speed log, but this was not observed in the rolling ratio of SOG/STW. It stands out that a peak in relative added power coincides with a peak in water temperature in mid-2019. However, it is unclear whether the observed seasonality can be exclusively attributed to marine growth. The overall magnitude of the propeller performance is relatively small and takes both positive and negative values despite the bias correction.

In Fig.8, the results of the semi-empirical method (SEM) and the machine learning approach are compared. Thereby it is understood that only samples with speeds within a range of ±3 kts around the mean speed are shown. This in turn leads to unavailable data during the COVID-19 period due to reduced operating speeds. However, the previously observed seasonality can be still identified in Fig.8.

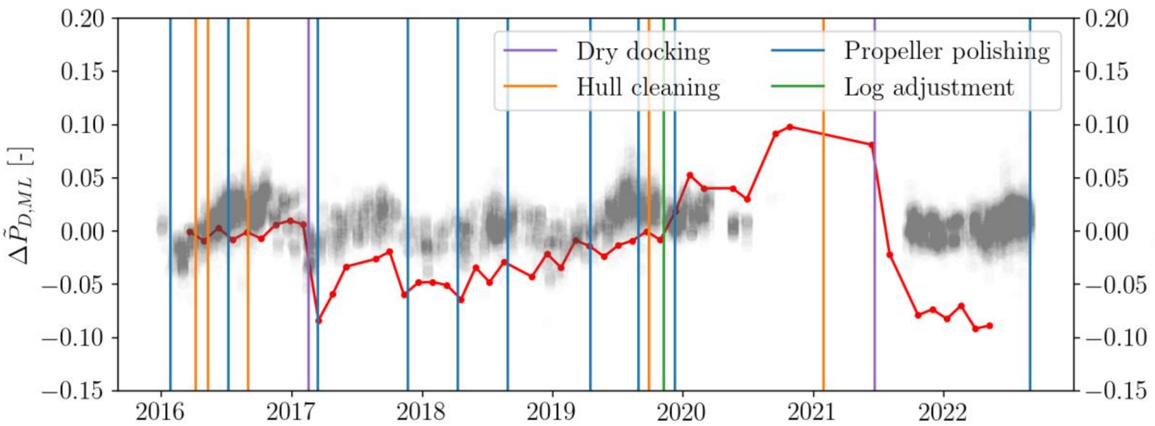

Fig.8: Isolated power increase caused by propeller fouling obtained through machine learning (primary axis) and the results of the semi-empirical framework in transparent grey color (secondary axis)

In view of Fig.8, it is stated that the machine learning-based propeller performance shows a profound correlation with the hull performance (cf. Fig.6). In contrast to the semi-empirical estimates, the cleaning effects of the individual dry dockings are visible in Fig.8. However, the variance of the machine learning KPI is too large for stating the same for the in-water cleaning events. Broadly speaking, both estimates show rough quantitative agreement in the first two dry-docking intervals, but a clear offset becomes apparent in the third interval, which may be caused by the speed log adjustment leading to a change in the relationship of the individual predictors and the target(s). Moreover, a larger predicted propeller contribution to the total ship performance is visible, as observed in Fig.6.

Based on the semi-empirical framework described in Sec. 3.2, it was calculated that a propeller roughness of k_P=150µm and k_P=300µm led to a relative added power of 3.7% and 5.6%, respectively. It is noted that these two roughness values reflect medium and heavy slime conditions, i.e. those conditions, which were observed (on the hull) in Fig.5. The order of magnitude of the theoretical values can also be observed in Fig.8. However, the average contribution of the propeller performance to the total performance appears to be relatively high in case of the machine learning results with 18.1%. The theoretical relative contribution of the propeller performance for the two mentioned roughness scenarios is 12.8% and 17.9%, respectively. Hence, the propeller contribution appears as relatively high in the case of the machine learning approach due to the frequent propeller polishings resulting in less fouling.

4.3. Discussion

The uncertainty and possible inaccuracies of the two benchmark methods have been pointed out previously and thus the uncertainty of the machine learning approach is of interest in this section. Uncertainty is commonly split into two categories: (1) ‘Epistemic’ or systematic uncertainty is due to limited data availability and reduces, as additional data is acquired. (2) ‘Aleatoric’ or statistical uncertainty, however, is an inherent part of the data and reflects the noise and variance within the data. Hence, the latter is unaffected by increasing data availability. Even though the case ship shows relatively good data quality, the sensor noise, i.e. aleatoric uncertainty, affects the obtained results. As shown by *Ikonomakis et al. (2021)*, the speed log for measuring *STW* is very error-prone and can show significant sensor drift. Similarly, *Mittendorf et al. (2023a)* showed that wind anemometers may show also a lower data quality including a bias depending on the wind direction due to turbulence and shielding effects due to, e.g. superstructures. Regarding epistemic uncertainty, there is a lack of reliable reference data, such as sea trial curves, but it remains unclear whether the performance decomposition via machine learning would increase in accuracy when having accurate baseline data. Moreover, no sensor data regarding the fin stabilizers were available and also the sea state is not considered in the present analyses. However, the ship sails in an area, which is known for hurricanes, and hence the sea state and the added wave resistance are crucial for performance monitoring in general. Crucially, the lack of any wake field information complicated the study of the isolated propeller performance in both cases.

A major drawback of machine learning approaches is opaqueness and, herein, it is attempted to provide a 90% prediction interval following the work of *Mittendorf et al (2022b)*. For this reason, the Monte Carlo (MC) dropout method, which is proposed by *Gal and Ghahramani (2016)*, is implemented in the presented machine learning framework. In short, dropout is a regularization technique, which randomly switches off certain neurons during training. MC dropout builds on keeping the regularization technique during testing and multiple stochastic forward passes provide ensemble predictions, which reflect model uncertainty. One major advantage of the MC dropout method is the straightforward implementation into an existing model, as it does not require a special training procedure. MC Dropout is a practical approximation of Bayesian inference in deep learning models and can be seen as a deep Gaussian process. The uncertainty estimate is useful in various applications, such as quantifying prediction confidence, identifying out-of-distribution samples, or enabling active learning. In Fig.9, 90% prediction intervals are provided for the KPIs of the machine learning model and ISO 19030. It is stressed that all machine learning models are subject to the tradeoff between transparency and accuracy. In fact, the implementation of MC dropout slightly reduces model capacity, which leads to different (less accurate) performance estimates, as compared to Fig.6.

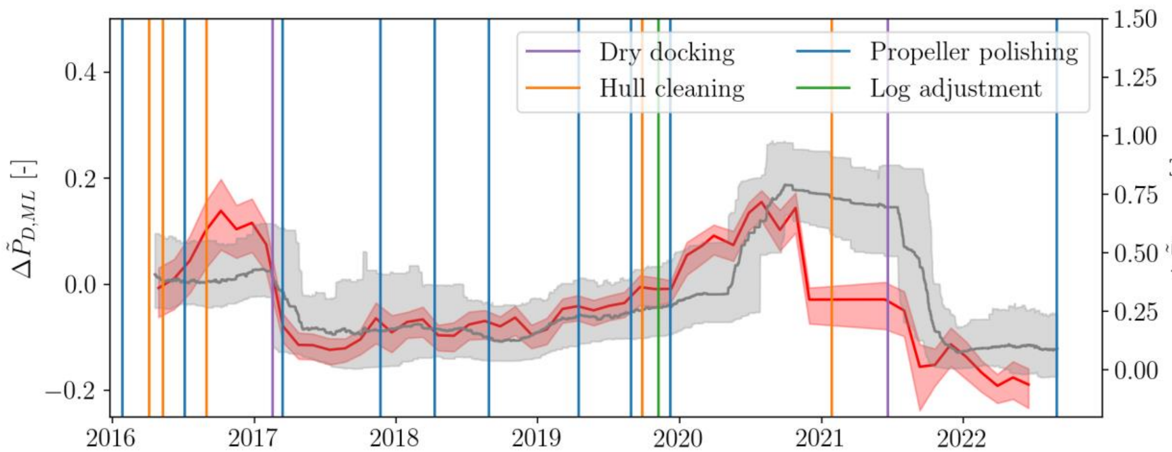

Fig.9: Overlay of the individual 90% prediction intervals derived from ISO 19030 (grey) and the machine learning framework using MC Dropout (red)

In view of Fig.9, it is stated that both methods still show qualitative agreement, but the performance indicator of the machine learning model shows a larger variance in direct comparison to Fig.6. Interestingly, the prediction interval of the machine learning model is not as wide as the corresponding one of the ISO analysis. This in turn could indicate that the estimator is able to model and correct for numerous physical phenomena caused by, e.g. trim or wind. This was also shown by *DeKeyser et al. (2022)*, where a machine learning model trained on sensor and metocean data was able to capture severe weather conditions sufficiently and seemed to be superior in comparison to empirical corrections, as recommended in ISO 15016, *ISO (2015)*. It is stressed that the training data of the machine learning model is not filtered based on weather conditions, as opposed to the ISO analysis. Ultimately, the uncertainty bounds increase industrial applicability for, e.g. voyage or speed optimization.

5. Conclusions

This paper presented a machine learning-based methodology for decomposing vessel performance into a hull and propeller component in an adaptive context. For this reason, 7 years of sensor data obtained aboard a larger cruise ship were utilized as a data stream. The obtained results were compared to two benchmark methods and it is emphasized that validation of a fouling indicator is delicate since it is a latent variable. Overall, the total performance indicator was in good qualitative agreement with ISO 19030 results, but the decomposition results are considered to be indicative at best. Particularly the comparison of the propeller performance indicator was not conclusive due to the relatively small magnitude of propeller fouling, the well-maintained case ship, and the inherent uncertainties regarding several sensor readings, such as *STW*. As concluded by *Paereli et al. (2016)*, the decomposition of hull and propeller performance requires the in-situ wake field for accurate and reliable results, which is up until now not feasible. Moreover, it seems promising to apply the shown methodology to a case ship with an installed thrust meter. For further extending work, it is appealing not to separate hull and propeller fouling, but rather the technical and environmental performance of the ship, which is realized by *Tvete et al. (2022)* with their VTI (Vessel Technical Indicator), which includes a detailed correction for environmental conditions, such as wind, waves, and water temperature. Additionally, the speed dependency of performance indicators is a well-known problem and hence a similar correction, as proposed by *Schmode et al. (2018)* bears sizable potential. The lack of reliable sea state data introduced uncertainty into the presented results, and hence acquiring wave parameters (or even the entire directional wave spectrum) directly from a wave radar setup or measured ship accelerations (and a set of transfer functions) following the wave buoy analogy (e.g. *Nielsen, 2018*) is an important aspect of future work.

As stated by *Farkas et al. (2021)*, the impact of the propeller surface per unit area is significantly higher in comparison to the hull surface. However, in absolute terms, the propeller surface area is very small compared to the hull surface. When considering the benchmark vessel KVLCC2, the propeller surface is less than 0.5% of the hull's wetted surface area. The degree of propeller fouling appeared to be of less importance compared to hull fouling in the present context and its magnitude as well as the lack of reliable reference (and wake) data impeded a dedicated monitoring approach. For all of the above, the practical relevance of isolating propeller performance is relatively low. Preventative (and proactive) maintenance of the propeller(s) is considered best practice due to the small and robust surface, i.e. it is cost-effective and does not damage the surface condition, as compared to hull cleanings. In general, it is advisable to conduct a propeller polishing in a quarterly or half-yearly rhythm.

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Fouling Prediction for Improving Hull Performance - Is it Possible?

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Abstract

In this paper we discuss the importance of having digital systems that could predict accurately enough the condition of the hull and support a vessel operator in planning inspections and hull cleaning in the most efficient way. We also discuss how such predictive systems could be developed and present two approaches. Studies have estimated that improved hull performance can reduce fuel consumption and CO2 emissions by up to 15%, this represents significant potential reduction in CO2 emissions given that the shipping industry is responsible for around 2.8% global greenhouse gas emissions. There are several strategies for improving hull performance, the most effective one being protecting the hull with special type of coatings which reduce friction and prevent biofouling from attaching into a vessel's hull. Although this approach has been used for many years, sometimes the protection from the coating is not enough for various reasons and therefore other measures need to be considered such as inspecting and cleaning the hull surface. The drop in hull performance can be attributed to various factors and the question of when the right time is to inspect the vessel is important. An inspection early, will lead to increased unnecessary costs and too late an inspection will lead to significantly increased cost due to an inefficient hull.

1. Introduction

Maritime transportation is an important pillar of the global economy. It is considered to be the most efficient mode of transportation per ton of goods and commodities carried, facilitating more than 80% of the international trade, *UNCTAD (2022)*. Shipping currently contributes approximately 2.89% towards global anthropogenic emission and is expected to continue the upwards trajectory due to continued growth of transport demand, *IMO (2020)*. IMO has progressively taken actions with key regulatory and implementation support steps since 2011 to combat climate change as part of UN (United Nations) Sustainability Development Goal.

One of the key factors leading to increased emissions and loss of vessel efficiency is associated to the resistance generated on the ship's underwater hull caused by marine biofouling growth and accumulation, *GloFouling (2022)*. Marine biofouling is defined as the process of accumulation of aquatic organisms immersed on surfaces in the aquatic environment, *IMO (2011)*. Biofouling growth on underwater hull increases resistance, roughness and drag; a function of seawater viscosity, velocity gradients developed in boundary layer and surface roughness, *Swain et al. (2022)*. The consequences of having a drop in hull performance will sequentially affect the operational, economical and carbon efficiency of a vessel.

When a vessel experiences speed loss due to fouling at constant power, they will either accept delays in schedule and loss of trading days, which will affect operational planning and efficiency, or power up to attain original speed to maintain schedule. This action of powering up will incur increased fuel consumption, thereby affecting operational expenditure and economical effectiveness of the business. Shipping bunker cost remains the biggest cost, constituting 50-60% of a ship's total operating cost, *Han and Wang (2021)*. The consequence of increased fuel consumption then results in increased carbon emissions to the air, which affects the efficiency of vessel emission per cargo-carrying capacity and nautical mile (CII Rating).

The impact of biofouling on energy efficiency has been well studied, and hull performance optimization is vital. Consider the recent study by GloFouling partnerships, a collaboration between IMO, GEF

(Global Environment Facility) and UNDP (United Nations Development Programme). They published a technical report in 2022 that highlighted that a layer of 0.5mm slime covering up to 50% of hull surface could trigger increase of GHG (greenhouse gases) emissions in the range of 25 to 30%, while more severe biofouling conditions like light layer of small calcareous growth could see 60% and medium calcareous for as high as 90%. Another study by *Swain et al. (2022)* estimated that the global ship emission can be reduced by up to 19% if vessels globally maintain smooth and foul free hull.

Marine biofouling has been a perpetual problem throughout history, dating back more than 2000 years, *Yebra et al. (2003), Myrsini-Dionysia et al. (2023)*. To overcome the problem of fouling, antifouling systems, defined as "a coating, paint, surface treatment, surface or device that is used on ship to control or prevent attachment of unwanted organisms", *IMO (2019),* have been extensively used. From the early Phoenicians and Carthaginians using pitch and possibly copper sheathing in ship's bottom, wax and tars utilized by the ancient Greeks in 300 B.C. *Myrsini-Dionysia et al. (2023)* to the modern version of biocidal self-polishing coatings and foul release coatings, the objective has been the same; to apply coatings to prevent the growth of fouling and maintain a clean hull. Today, there are estimated 4,000 different identified fouling species across the ocean, *Yebra et al. (2004), Arai (2009)*. As foulants individually adapt to coexist and live in specific environments, they pose a challenge to select suitable antifouling systems designed for pre-defined trade, operational parameters, and in-service intervals. The absence of a fixed trading pattern due to open markets (unknown cargo and route ships under management), spot trades and dynamic business outlook also increases the challenge for selecting the most efficient type of antifouling system, *Dekinesh (2018)*. The misalignment of actual trading parameters from design will also compromise the coating efficacy, therefore other measures will need to be considered such as inspection and cleaning the hull surface to hedge the fouling risk.

Underwater inspection and cleaning is another conventional method to maintain a clean hull. The initial cleaning work is performed by workers to remove fouling by hand. Like antifouling technology, inspection and cleaning methods have also evolved tools which increase efficiency, safety and reduce labor intensity. Remotely Operated Vehicles (ROVs) can conduct inspections as well as cleanings at a comparable standard to traditional diving operations, *Song and Cui (2020)*.

With the regulators shifting emission targets from the initial IMO GHG strategy in 2018 of achieving 70% reduction by 2050 (of 2008 emission) and total annual emission of at least 50%, *IMO (2020)* to a significantly higher target of 20% reduction in emission by 2030, 70% reduction by 2040 (compared to 2008 levels) with the goal of achieving net-zero emissions "by or around, i.e., close to, 2050", *IMO (2023)*, there will inevitably be challenges, but also opportunities for the industry to find more effective and efficient ways to manage fouling risk by exploring beyond conventional solutions. Adoption of digitalization and multi-disciplinary approaches to build solutions must be considered to resolve the age-old fouling problem.

This paper will discuss the importance of adopting digital systems to accurately predict the condition of a hull, hence augmenting the role of antifouling coatings to support vessel operators in planning for inspections and hull cleanings that achieve optimized hull performance and meet regulatory demands. Challenges of having such systems will also be discussed.

2. Digital era in maritime transportation

Maritime transportation is lagging in the digitalization transformation as compared to other industries when assessed against 8 domains of digitalization based on technology trend in 2018-2019: Autonomous vehicles and robotics, Artificial intelligence (AI), Big data, Virtual and Augmented Reality, Internet of Things (IoTs), Cloud and Edge Computing, Digital security, and 3D printing, *Sanchez-Gonzalez et al. (2019), Timimi (2021).* The focus on change in the maritime industry has been increasing, despite slower adoption. Digitalization is already transforming shipping companies' operations and business strategies through the utility of data to develop novel business logic like decision support systems with faster processing and higher volume of data for operation optimizations and new business models, *Lambrou et al. (2019), Gaspar and Fonseca (2020).*

In the context of marine biofouling, it is important that the digital solution can assist in providing timely and quality intelligence through active hull condition monitoring to maintain hull performance. Optimized hull performance will reduce speed loss, over consumption of fuel and unnecessary maintenance operations, *Coraddu et al. (2019)*. Hull performance analysis is not new to most vessel owners. The accessibility of data collection has paved the way for advancement in analytics. AIS-log files, meteorological data, vessel on-board data, etc. are large data sources available to the shipping industry, which can be aggregated and processed using big data analytics, *Fruth and Teuteberg (2017*). There has been a progressive shift from the traditional methods in the early stages, which involved manual data collection (noon-reporting) with the simplified correlation between ship speed, fuel consumption and other parameters, to assess the hull's performance. The emergence of ISO 19030 – Measurement of changes in hull and propeller performance in 2016 have provided a standard for the measurement, monitoring and assessment of ship hull and propeller performance with procedures for data collection, analysis, and reporting, allowing for consistent and comparable analysis across the industry. There is work still to be done to reduce uncertainties in the methodology. Despite them, there is no other typical way except monitoring speed to power relationship in service for predicting performance drop due to fouling, *Erol et al. (2020*), and acting when the speed deviation trend drops to a specified level in accordance with one of the performances indicators put forth by ISO 19030: maintenance trigger.

The digital transformation on underwater inspection and cleaning will be the utilization of robotics and remotely operated vehicles (ROVs) to perform the task of inspection and/or cleaning. The advent of ROVs certainly improves the efficiency and effectiveness of inspection and cleaning. Combined with proactive measures of frequent periodic cleaning, studies found that this proactive approach is effective in maintaining hull performance. Energy efficiency estimation based on fuel consumption before and after cleaning of a 5 years old aframax crude oil tanker showed a 9% to 17% reduction in daily fuel consumption, *Adland et al. (2017). GloFouling (2022)* technical paper estimated a savings of $6.5 million over a period of 5 years for a 40,000 DWT bulk carrier by adopting similar proactive frequent periodic cleanings.

The pertinent question then, for inspection and cleaning, will be on the timing of assessment. Getting the right timing to conduct inspection and cleaning is crucial. Inspection or cleaning too early leads to increased unnecessary costs while cleaning too late will result in a significant impact on a hull's performance. Whilst periodic scheduled cleaning sounds intuitive, there are still inherent issues related to the frequency of cleaning: what is the basis of spending time to conduct inspection? Is there a real need based on intelligence? Nevertheless, this proactiveness does pave the way for the eventual utility of big data and the possibility of utilizing real-time data for fouling prediction to provide well timed and high-quality intelligence to establish evidence-based maintenance regime.

To advance the development of fouling predictive analytics, understanding the fouling construct and its primary parameters are of paramount importance. Research has been done in this field, and the primary parameters can be categorized under three groups: Physical and chemical properties of water; physical and chemical characteristics of hull surface layer and climatic and geographical conditions, *Tarelko (2015)*. The success of developing reliable fouling predictive analytics is hinged on the ability to identify patterns, correlations and assigning the right weightages to the primary parameters since not all parameters have similar impact on biofouling growth at any given configuration.

In essence, we can combine conventional fouling protection strategies with digitalization to good effect. The combination of suitable antifouling, active hull condition monitoring and inspection with cleaning will enhance hull performance. In another words, digitalization of hull performance opens a new world of opportunities to move from a reactive state of being to a predictive and proactive phase of maintaining hull performance with tangible benefits as seen from the real-life cases that follow.

2.1. Benefits of a fouling predictive system on a 300,000 DWT Crude Oil Tanker

Jotun performed ISO 19030 hull performance analysis and used an in-house developed fouling risk algorithm to assess the impact of such a system. As seen in Fig.1, additional power (%) needed is seen over time. Vessels have received 2 fouling risk alerts with 'inspection recommendation' based on fouling risk algorithm. The first period, after the alert, did not appear to have a significant impact on vessel performance, and the additional fuel impact due to additional power required was $17,000 USD on average as compared to the benchmark at $400 USD per ton. However, the second period, after the 2nd alert, saw a significant increase in additional power that resulted in an additional $572,000 in fuel consumption. In retrospect, the first period was the initiation of early stages of fouling which contributed negatively to the second period. The accumulated fouling pressure over the course of the first 2 years sailing interval coupled with the prevailing high fouling risk exposure in 2nd period trade ultimately resulted in the high fuel penalty. The total penalty for the 2 combined periods was an additional 1,472 tons of fuel and 4,578 tons of CO_2.

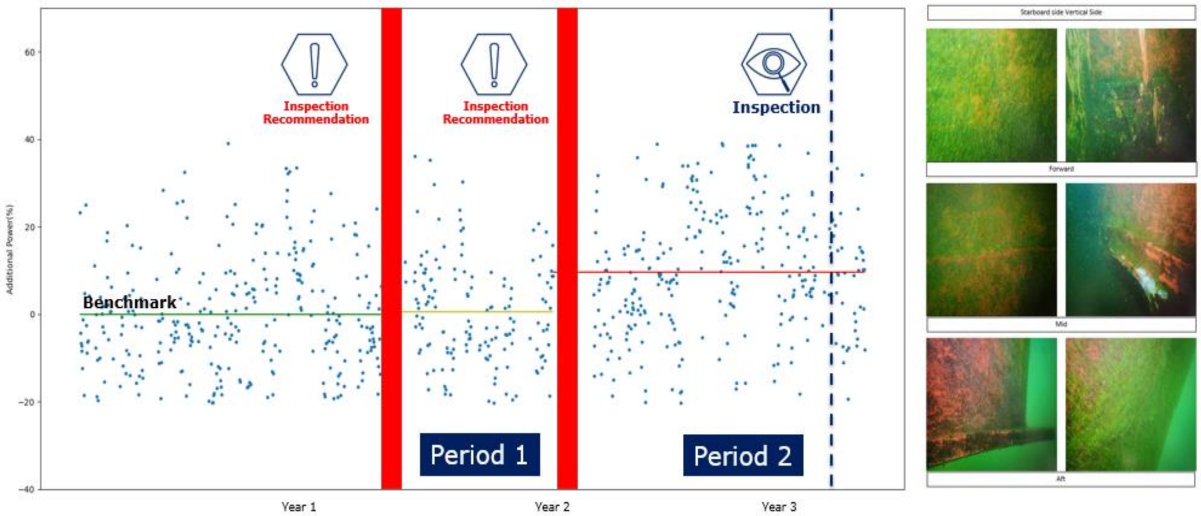

Fig.1: Additional power over time overlapped with suggestions from a predictive fouling risk system

2.2. Benefits of a fouling predictive system on a 300,000 DWT Crude Oil Tanker

Jotun performed ISO 19030 hull performance analysis and utilized Jotun HullKeeper fouling risk algorithm to analyze the predictive alert in time series to assess the impact of period 1 with the benchmark period in the graph.

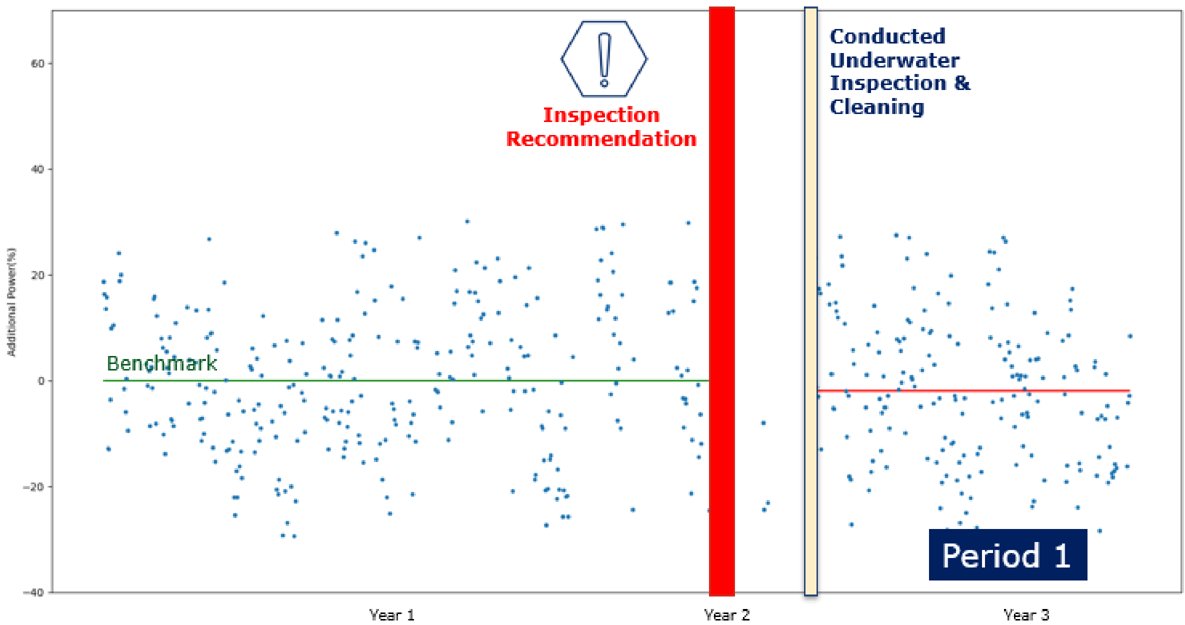

Fig.2: Additional power over time overlapped with suggestions from a predictive fouling risk system

The vessel received a fouling risk alert with ‘inspection recommendation’ based on the fouling risk algorithm. There was a gap of 2 months between the alert and inspection with cleaning. The vessel was then continuously evaluated during the first period after inspection and cleaning. The result shows that early intervention with the fouling risk algorithm’s inspection recommendation has allowed ship operator to act with reliable intelligence to maintain hull performance. A marginal statistical improvement in performance was also observed.

3. Challenges of a fouling prediction algorithm

All surfaces submerged in seawater will experience, at a certain point in time, fouling of organisms such as bacteria, diatoms, algae, mussels, tube worms and barnacles. Marine fouling is the undesirable accumulation of microorganisms, algae and animals on structures submerged in seawater. The fouling organisms can be divided into microfouling (bacterial and diatomic biofilms) and macrofouling (e.g., macroalgae, barnacles, mussels, tubeworms, bryozoans) which live together forming a fouling community. In a simplistic overview of the fouling process, the first step is the development of a conditioning film where organic molecules adhere to the surface. This happens instantaneously when a surface is submerged in seawater. The primary colonizers, the bacteria, and diatoms, will settle within a day. The secondary colonizers, spores of macroalgae and protozoa, will settle within a week. Finally, the tertiary colonizers, the larvae of macrofouling, will settle within 2-3 weeks.

Fouling prediction algorithms try to mathematically model the presence of fouling (type and extent) on submerged surfaces. Predicting a biological phenomenon (accumulation of fouling to a surface) is always a challenge, as it is a highly complex multidimensional problem with multiple parameters to consider. In this paper we will focus and discuss possible approaches for a fouling prediction algorithm on seagoing vessels’ hulls. Most importantly, the submerged surface is not idle, moving at speeds where mechanical forces through the flow of water cannot be neglected. This increases the complexity of the problem by many degrees. In addition, seagoing vessels are sailing into different geographical areas exposing the surface to completely different biodiversity and environmental factors when moving from one area to another. Furthermore, a vessel hull is such a big surface with different roughness and curvatures which do not allow for a uniform distribution of fouling accumulation, making the need of separating the surfaces into smaller areas necessary. Finally, vessels hulls are protected by special coatings that are carefully designed to prevent microorganism from attaching to the surface and contain biocides that kill the ones that attach. These coatings may have a significant influence in the presence of fouling and under certain conditions keep a hull clean for a significant period (up to 5 years).

Accumulation of fouling on a surface is influenced by many factors and until now no exact rule can be used to determine the fouling growth, even if indications have been found that the theory of opportunities considering pressure, shear and turbulence can be applied as per *Alamsyah et al. (2020)*. After *Mullineaux et al. (1993)* two main requirements need to be fulfilled for the biofouling attachment instincts to function properly. First, environmental disturbance should be minimum (shear stress, turbulence), and second, the instinct to attach to moving surfaces. Those requirements seem to be in contradiction to each other, however a moving surface is preferred over a fully static one, increasing the likelihood of sufficient food supply.

For the biofouling growth three main factors are described, the supply of food ingredients, food filtration mechanisms and food digestion. A hydrodynamic condition supporting the above three processes is favorable for growth and will also influence the structure, morphology and distribution of fouling. Food supply and food filtration (food filtering and identification most of the time by antennas) will be more difficult in a highly turbulent flow, where there are high shear stresses and shorter time for food identification and disturbed digestion.

For ships the hydrodynamic condition is highly influenced by speed through water, the hull shape; which influences distribution of shear and pressure forces, and the voyage factor. A hydrodynamically favorable situation for antifouling growth is a low shear force however with a slowly moving surface not faster than 10 kn as per *Coutts et al. (2010)*. Above a velocity of 18 kn, *Coutts et al. (2010)* showed that most of biofouling gets removed if it was not already colonized, encrusted, hard and/or very flexible in its morphological characteristics.

As previously mentioned, additional dimensions from the external environment need to be considered when developing a fouling prediction algorithm. Today, there are estimated 4,000 different identified fouling species across the ocean, *Yebra et al. (2004), Arai (2009)*. Environmental parameters significantly affect the presence and the behavior of so many species. More specifically, it was highlighted that high sea water temperature increases the rate at which fouling develops. In addition to water temperature, nutrients such as phosphates, nitrates and carbonates are found to be important in the existence of fouling species both for plant and animal fouling. Availability of light is also important, as light acts as an energy source for plant fouling absorbing light and converting into new organic matter which can further be used as source of food for animal fouling. High correlation between distance to shore and water depth was also reported. Finally, there are many local variations which play a role in the presence of fouling, driven by seasonality, biodiversity, local currents, geography as such, salinity and others, which are very hard to consider partly because their exact effects are not known and partly of no availability of relevant data. As discussed before, the problem becomes even harder as seagoing vessels travel to various geographical areas exposing their hulls to multiple fouling species and environmental conditions.

Another aspect that should be considered when trying to predict the presence of fouling into a vessel's hull is the actual shape of the hull. The hull is a very big surface with a lot of variability in curvature and roughness, both of which can have a significant effect on fouling processes. Curvature, for example, can affect fouling by altering the flow patterns and fluid dynamics near the surface. In general, highly curved surfaces tend to promote higher fluid velocities and increased turbulence, which can reduce the presence of fouling by enhancing the shear forces that hinder fouling deposition. The curvature of the hull can also affect the availability of light, which as discussed previously acts as a catalyst to fouling growth. Roughness is also another characteristic of the surface that influences fouling. Experimental data shows that there is a tendency for smooth surfaces to attract less biofouling than surfaces with more substantial roughness. This could be explained because rough areas most probably act as a "shelter" to microorganisms in a microscopic level. It is obvious that local characteristics of the hull surface contribute to the presence of fouling, and within the context of a fouling prediction algorithm, one should consider developing different predicting models for different parts of the hull.

All the above dimensions that contribute positively or negatively to fouling accumulation play an important role, but it is difficult to distinguish their importance based on available data. However, it is undisputable that specially designed coatings for the underwater part of the hull can be a differentiation factor. These coatings are designed to mainly release substances/biocides (in a controlled way) which prevent microorganisms from settling/growing. There are multiple technologies and approaches. *Gelegenis (2019)* summarizes them in a very good way, but it is very difficult to model how these coating work. Their compounds, substances and raw material are not publicly available nor are there actual chemical processes/mechanisms that take place when the coating interacts with the sea water. As previously mentioned, these special coatings can maintain a clean hull for up to five years and can be a differentiation factor. A fouling prediction algorithm should try to simulate or model the coating behavior. In such an approach, coating manufacturers have an advantage as they have the necessary knowledge to model coating mechanisms and the experimental data to validate the latter. One should also consider that some of the environmental parameters mentioned above (ex. sea water temperature) affect the mechanisms of the coating as such.

Another dimension to consider when developing a foul prediction algorithm is what exactly one should try to predict. As previously mentioned, there are two important types of fouling, one is plant based and the other is animals and are found to have different impacts on vessel performance, *Schultz (2007)*. Therefore, predicting the type of fouling or going one step further and predicting the actual species should be of interest, especially now, that most probably new regulations will soon come into force regarding biofouling management and the prevention of transfer of non-indigenous species. However, it is equally important, or even more important, to predict the extent of fouling (in percentage) of the area(s) of interest. *GIA (2022)*, a project hosted by International Maritime Organization (IMO) published a report mentioning that different extent of fouling with the same type of fouling can have an impact in Green House Gas Emissions up to 20%. Given the high impact in vessel efficiency and in the environment, a fouling prediction algorithm should try to predict both type and extent of fouling which increases the complexity by many degrees. It is a bit dependent on the use case and operational needs.

At this stage it is important to highlight and emphasize the importance of the use case. How will this algorithm be used and what are the operational needs? Such an algorithm will probably be used as an extra input for the right time to do maintenance. Maintenance regarding fouling is either an underwater hull cleaning, or a drydock to wash, blast and repaint the vessel hull. There are a lot of operators who have a proactive approach whereas some others prefer to do maintenance as soon as they can measure significant impact in performance. There is no right or wrong approach, however the approach should affect the method, and the parameterization of the fouling prediction algorithm. For example, in a proactive approach, the algorithm should be able to accurately predict very early stages of fouling, whereas in a more reactive approach the algorithm should be able to accurately predict when the vessel has a fouling extent of higher than 20-25%. In a more holistic approach, parameters such as drydocking period, lifetime of the vessel and maintenance budget should be included as inputs in the fouling prediction algorithm. In such a predictive maintenance approach, the algorithm becomes an optimization problem, and the algorithm is tuned to minimize maintenance costs.

One final point of discussion is the problem of dimensionality. Fouling is a physical phenomenon that does not occur instantly. It is a physical process the results of which can be observed in a specific moment in time, however the observations are the result of accumulation in time and historical operational parameters. Observations at any given point in time could be the result of what happened in the last x days, last x months or from the beginning of the period of interest. Identifying the period that has the biggest influence in accumulation of fouling is a very difficult problem and can be a separate study. In addition to this, if one thinks in a very simplistic way, a vessel sailing for just 1 year would have 365 dimensions (the input values for each day would be considered as different dimension). Such highly multidimensional problems are not yet easy to solve. Furthermore, most probably, the majority of these dimensions would have minimal or no influence at all on the final observation, therefore this approach most probably should not be followed.

It is, however, a challenge that should be addressed. Most probably the best way to address the dimensionality problem is to identify the necessary aggregation that would best describe the historical processes that have already occurred. For example, one could take the average or median values for the period of interest or after feature engineering and domain knowledge identifying periods that are most significant and aggregate only on these periods. Another approach could be that accumulation of fouling is a result of harsh conditions and failure points (for example failure of coating). If such assumptions are true, then maybe 70% or even 90% percentiles could be more appropriate. The challenge remains. What is the correct aggregation and what and how long is the correct period to aggregate?

To recapitulate, it should be obvious from all the above that we are discussing about a highly multidimensional problem, with a lot of unknowns and uncertainties of the actual phenomenon and with a lot of parameters interacting with each other in a different way given the conditions. In this paper two fouling prediction algorithms, using simple approaches will be presented and will be evaluated if simple approaches can bring value to the decision making. Going into more advanced approaches (which seems obvious, given the complexity of the problem) is out of the scope of this paper, but it could be discussed as a continuation of current work.

3.1. The dataset

To develop a fouling prediction algorithm, researchers typically start by collecting data on fouling at various locations and under different conditions. This data is then used to train the algorithm to recognize patterns in the data and make accurate predictions. In our case, the available dataset contained mainly observations from underwater hull inspection of seagoing vessels.

More specifically, the available dataset consisted of 215 seagoing vessels containing tankers, bulkers, some containers and car carriers. There were 1222 inspections carried out, unfortunately not evenly distributed for each vessel. While some vessels have up to 13 inspection reports in a docking cycle, which contributes significantly to understanding accumulation of fouling on the hull over time, most vessels have 2 to 4 inspection reports in a docking cycle. These inspection reports were thoroughly analyzed by technical advisors and assigned a rating. The rating is based on the type of fouling that has accumulated on the hull and the extent of it, which ranges from 0-100%. The 4 categories of fouling types used were thin slime, thick slime, short plant, and long plant. Fouling extent and type of fouling will be the value that the model should predict.

Predicting two features, such as fouling extent and fouling type increases the complexity of the model. To simplify the problem a simplest scale was introduced. The predicted value has been converted to a simple value from 1 to 10 called Fouling Factor and the goal was to combine in one scale type of fouling and extent in percentage. The conversion was done as seen on Table I, based on *US Navy (2006)*. Doing this conversion imposes extra uncertainty, however for the scope of this paper the uncertainty imposed is believed to be much less as compared to the complexity that is introduced by predicting extent and type of fouling at the same time.

As input to the model there were several parameters available, starting with AIS data. AIS stands for Automatic Identification System, and AIS is an automatic tracking system used in the maritime industry to enhance the safety and efficiency of vessel operations. AIS data provides information about the position of the vessel, along with speed, heading and course. Given that the position of the vessel is known, further environmental parameters (analyzed further below) can be extracted. AIS data is captured at a frequency of 10 minutes on average, but collecting such a high frequency of data would impose computational challenges. To reduce longer processing times for training machine learning models, the raw AIS data, with the 10 minutes frequency, was aggregated to a daily frequency.

Table I: Conversion matrix for a simple rating (Fouling Factor)

Fouling Factor	Thin Slime	Thick Slime	Short Plant	Long Plant
1	10%			
2	25%	5%		
3	50%	15%		
4		25%	50%	
5		25%	50%	25%
6		50%		50%
7		25%		75%
8		25%		75%
9				100%
10				100%

As further input a parameter called fouling pressure (FP), which is an output of a model developed by Jotun to quantify the harshness of environmental condition a vessel's hull faces every 24 hours, was added. The model uses a lot of available environmental parameters and tries to combine the impact of all these parameters into one value.

It ranges from 0 to 1, where 0 represents low risk seawater conditions in terms of accumulation of fouling, while 1 is the other extreme. Accumulated fouling pressure is the FP's cumulatively being added everyday till the day of the inspection and this is the value that was used as input to the model. This accumulation resets back to 0 only if a cleaning of the hull has taken place, or the vessel is docked.

Another important parameter that needs to be considered and highlighted is the effectiveness of the hull cleanings. If a hull cleaning had taken place in-between drydock intervals of a vessel, the quality of the hull cleaning should have been reported. This is because hull cleaning affects the protective coating's performance on the hull. If the cleaning process has not been conducted with soft tools, it is likely that a layer of protective coating would be polished off or destroyed during the cleaning process, thus decreasing the overall thickness, effectiveness, and lifetime of the protective coating. Since the quality of cleaning was not reported with the inspection reports, two approaches were tested. First, where the cleanings are assumed to be carried out perfectly and second, where all inspection reports after the first cleaning are ignored.

Additional environmental parameters extracted from the vessel position at a certain point of time were also available as inputs. Sea water temperature (TEMP), distance to shore (DIS), water depth (WD), chlorophyll-a concentration (CHL), salinity (SAL). All these parameters as analyzed in previous chapters are known to have some kind of direct or indirect effect in the accumulation of fouling. For simplicity reasons, the mean value between the period from one inspection to another was used for all these parameters, however future work for this project could be to evaluate what other aggregated value can be used instead of the mean.

As previously mentioned, one of the most important parameters that controls fouling is of course the protective coating as such. Since there were more than 100 protective coatings in our dataset it is impossible to model the behavior of all these coatings. That is why two parameters called Coating category (CC) and a simplification of it called modified coating category (MCC) was introduced. CC ranges from A to F whereas A is ultra-premium, and F is a market average protective coating. MCC uses 3 categories namely low, medium and high. The reason to introduce this parameter is to aggregate all these products based on reported performance. Doing this, imposes some extra uncertainty as the categorization is not based solely on facts and it is somewhat subjective, however and within the scope of this paper the benefits in reducing dimensionality most probably overcome the uncertainty imposed using this parameter.

Finally, there were some parameters which are derivatives of the available input parameters which are believed to have some kind of impact on the accumulation of fouling. Coating age (AGE) is known to have an impact as it is generally proven that performance of a protective coating is deteriorating over time. Accumulated hours below 6 kn (S-HR), number of stops (NOS) and duration of longest stop (DLS) are also parameters that needed to be considered as the risk increases significantly when the vessel is idling or moving at very low speeds.

3.2. A simplistic approach as baseline

To be able to check foul prediction results, a simplistic model was constructed to be used as a baseline. In addition to this, there was a need to evaluate whether a simplistic approach could already bring value to the operator. In order to come up with a simplistic model we decided to use a decision tree. As per https://en.wikipedia.org/wiki/Decision_tree, a decision tree is a decision support hierarchical model that uses tree-like model of decisions and their possible consequences. It is one way to display an algorithm that only contains conditional control statements.

In that decision tree it was decided that the first important parameter is the coating age. There was a strong correlation between coating age and fouling factor and from the dataset available it seemed like performance was dropping after the 3^{rd} year of the drydocking cycle. In addition, the coating category was selected as the second most important parameter and finally the number of days idle. The decision tree can be seen in Fig.3. If a vessel with a certain coating age and a certain coating category was exceeding a certain threshold of idle days, the vessel should be inspected. In any other scenario the vessel's hull was considered to be in good condition. The reason why this approach was selected is that it simulates a simple reasoning that was used for many years by operators for decision making in maintenance of the hull.

The model was evaluated based on fouling factor. Under the assumption that any vessel rated higher or equal to 3 in fouling factor should be inspected, it was very simple to compare the results of the model against the actual results. Out of 1222 inspections, 697 were found to be like reality and this is an accuracy of 57%. This is slightly better performance from a model selecting randomly whether a vessel should be inspected or not and obviously not a good approach for a fouling predictive system.

3.3. A machine learning approach

As an alternative approach to the decision tree, more advanced machine learning algorithms (ML) were chosen. In a typical data science project, multiple combinations of the available parameters are tested, and the models created compete among each other based on evaluation metrices. In these numerous combinations of the parameters mentioned in chapter 3.1 were used as training datasets, to predict Fouling Factor, for machine learning (ML) models. Two famous machine learning algorithms were chosen to serve this purpose: XGBoost and Artificial Neural Networks (ANN).

XGBoost stands for "Extreme Gradient Boosting" and it has become one of the most popular and widely used ML algorithms due to its ability to handle large datasets and its ability to achieve state-of-the-art performance in many ML tasks such as classification and regression, https://www.geeksforgeeks.org/xgboost/. XGBoost has built-in support for parallel processing, making it possible to train multiple models in a reasonable amount of time, https://www.geeksforgeeks.org/xgboost/. What gives XGBoost its 'X-factor' is its ability to provide insights into feature importance, allowing researchers to understand which features contribute the most to the predictions. This assists in feature selection and understanding the underlying relationships in the training dataset.

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of the human brain. They are composed of numerous interconnected processing nodes, or artificial neurons, that can learn to recognize patterns in data, https://www.aiforanyone.org/glossary/artificial-neural-network. ANNs can be trained on large datasets and can implicitly detect complex nonlinear relationships between dependent and independent variables, https://www.researchgate.net/post/What-are-the-advantages-of-using-Artificial-Neural-Network-compared-to-other-approaches.

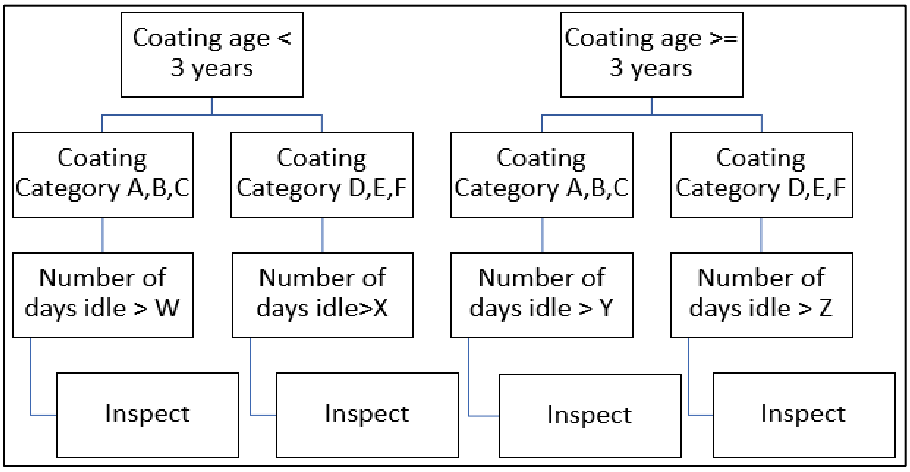

Fig.3: Decision tree for inspection recommendation

XGBoost and ANN ML approaches were used to create numerous models with different sets of training parameters. However, both algorithms are strongly dependent on some parameters called hyper-parameters. Hyperparameter tuning is a know0n challenge in data science. It refers to the process of selecting optimal values for the parameters of an ML model. These parameters are not learnt from the data but set before the training process. They control the behavior of the learning algorithms and influence how the model is trained and how it generalizes to unseen data. Finding the optimal combination of hyperparameters can lead to improved accuracy, better generalization, and more robust models. It allows the model to better capture the underlying patterns in the data and avoid overfitting or underfitting.

Hyperparameter tuning was also implemented on the ML models to improve their accuracies. For every 1000 tunings of XGBoost models, 50 ANN models were tuned. This was solely done because of the shorter training times of the XGBoost models.

Table II: Results of top 5 best performing ML models

	Data included after cleaning		Data removed after first cleaning	
Model and Input Parameters	XGBoost (RMSE)	ANN (RMSE)	XGBoost (RMSE)	ANN (RMSE)
M1: FP, AGE, CC	1.63	1.70	1.68	1.78
M2: CC, AGE, S_HR, TEMP, CHL, WD, DIS	1.63	1.88	1.62	1.96
M3: CC, AGE, S-HR, TEMP, CHL, WD, DIS	1.61	1.73	1.66	1.85
M4: MCC, AGE, S-HR, TEMP, CHL, WD, DIS	1.60	1.71	1.66	1.84
M5: FP, AGE, CC	1.66	1.66	1.75	1.75

On Table II, top 5 in terms of predicting results ML Models with both algorithms are presented. The metric to evaluate the models that were created was Root Mean Square Error. The standard process of any machine learning approach was followed where the dataset was split into 80% training set and the results were evaluated against the 20% test set. As seen from the table all top 5 models show no significant difference in their accuracy and in terms of Mean Absolute Error these results are roughly in the range of 1.4 as mean absolute error in fouling factor.

Other general observations from the tests are that XGBoost models generally outperformed ANN models in terms of accuracy. This could maybe be explained by the fact that XGBoost models take significantly less time to train, so more combinations of hyperparameters were used for optimization. It was also observed that including inspection reports after cleaning, even if the quality of cleaning is unknown, into the training dataset improved the accuracy of the models.

The same evaluation as the decision tree approach was followed using the best performing model. Using only the Test set, this time consisting of 241 inspections and under the assumption that any vessel with foul rating higher or equal to 3 should be inspected, 159 were found to be accurate. This is an accuracy level of 66%. This is a better result than the decision tree approach.

3.4. Conclusion

The main scope of the paper is to identify whether a simplistic approach or a machine learning approach is good enough to support decisions regarding maintenance events, mainly inspections and eventually cleaning if needed. As mentioned earlier, the decision tree approach achieved an accuracy of 57%. In the ML approach, the accuracy achieved was 66%.

At this stage, cost is becoming a very important factor and due to lack of data in that area, this type of analysis exceeds the scope of this paper. However, one should consider adding cost parameters into the models and change the approach to optimize the model for cost minimization. In such approaches, there are many other parameters related to vessel operations that should be considered and analyzed.

One more thing to note is that there were several combinations that were tested and the difference of RMSE was varying from 1.6 being the best to 1.89 being the worst for XGBoost. The range in RMSE regarding ANN models was very similar. The small range in errors regardless of the input is an indication that it is possible that the problem (of fouling prediction) cannot be solved with the existing parameters. In such cases, one may need to consider additional parameters of factors that could affect the outcome. It might be necessary to gather more data, conduct further research, or explore alternative approaches to gain a better understanding of the problem and potentially find a solution. Additionally, if the problem is complex or poorly understood, it could indicate the need for more advanced or sophisticated models, techniques, or methodologies to address it effectively.

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Correction Factors for CII Calculations – Saving Potentials with High Quality Sensor Data

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Abstract

The MEPC Res. 355 (78) provides the application of correction factors in the determination of the Carbon Intensity Indicator (CII), with the intention to substitute energy-intensive cargo such as frozen food products and liquified gases from CII calculation. This paper elaborates on the prerequisites in terms of the energy data acquisition technology required, which at the same time provides the technical basis for a holistic optimisation of the vessel's operation.

1. Important Milestones of IMO Greenhouse Gas Strategy Regulatory Framework in a nutshell

With the global drive for decarbonization the shipping industry is facing the challenge to comply with more stringent regulations related to greenhouse gas emissions (GHG). At the 80th session of the Marine Environment Protection Committee the previous in 2018 released targets have been tightened significantly. While the former regulation has defined a greenhouse gas reduction by 50% of 2050 compared with the level of 2008, MEPC 304 (72) (imo.org), the latest amendment, MEPC 377 (80) (imo.org), calls for a reduction relative to 2008 of:

- 20% and striving for 30% by 2030
- 70% and striving for 80% by 2040
- 0% by 2050

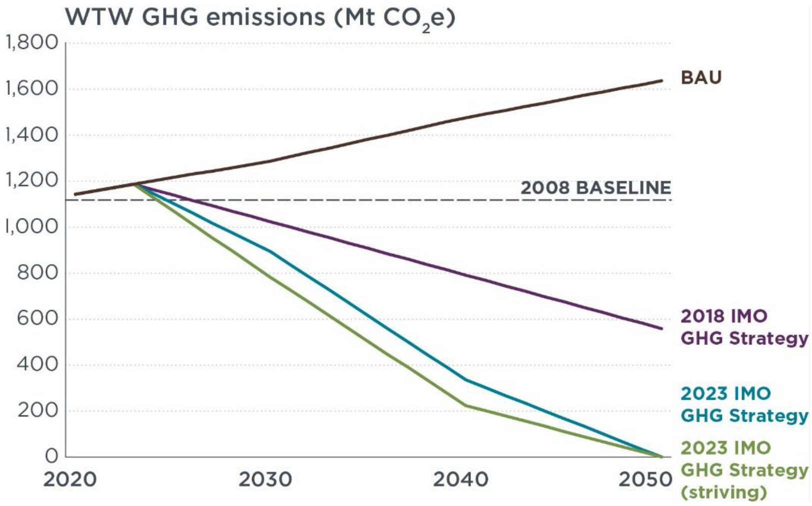

Fig.1: Well-to-wake GHG emissions pathways implied by the revised (2023) strategy compared to the initial (2018) strategy, the emissions in 2008, and business-as-usual (BAU) emissions, source: *Comer and Carvalho (2023)*

Most important milestones for the implementation of GHG targets in the past were the introduction of the Energy Efficiency Design Index (EEDI), and the Ship Energy Efficiency Management Plan (SEEMP) resolved in 2011, MEPC.203 (62) (imo.org), and entered into force on 1st of January 2013. This was followed by the introduction of Energy Efficiency Existing Ship Index (EEXI), EEXI and CII (imo.org), resolved in 2018 and set into force on 1st of November 2022. EEDI and EEXI are measures of the energy efficiency of the design of a vessel and technology on board, and do not indicate how the vessel is being operated. These indicators just represent the expected CO2 emissions per cargo ton and mile based on the vessel's engine power, cargo capacity and speed.

2. CII – Carbon Intensity Indicator, Correction Factors and Voyage Adjustments

Different from the previously mentioned measures, an assessment of the operational carbon intensity of ships was considered for the first time in MEPC Resolution 339 (76) in June 2021 by introducing the Carbon Intensity Rating (CII). The first year of the attained annual operational CII verification will be 2024 for the operation in calendar year 2023. Fuel consumption data, which is mandatory to be reported for vessels of 5,000 GT analogue to the IMO Data Collection System (DCS), IMO Data Collection System (DCS), since beginning of 2019 shall serve the data basis this.

The data is evaluated in an assessment and depending on the specific type of the vessel, an environmental rating of the CO2 emissions according to grades A (major superior) to D (minor inferior) is assigned. The thresholds for classification will become increasingly stringent over time until 2030.

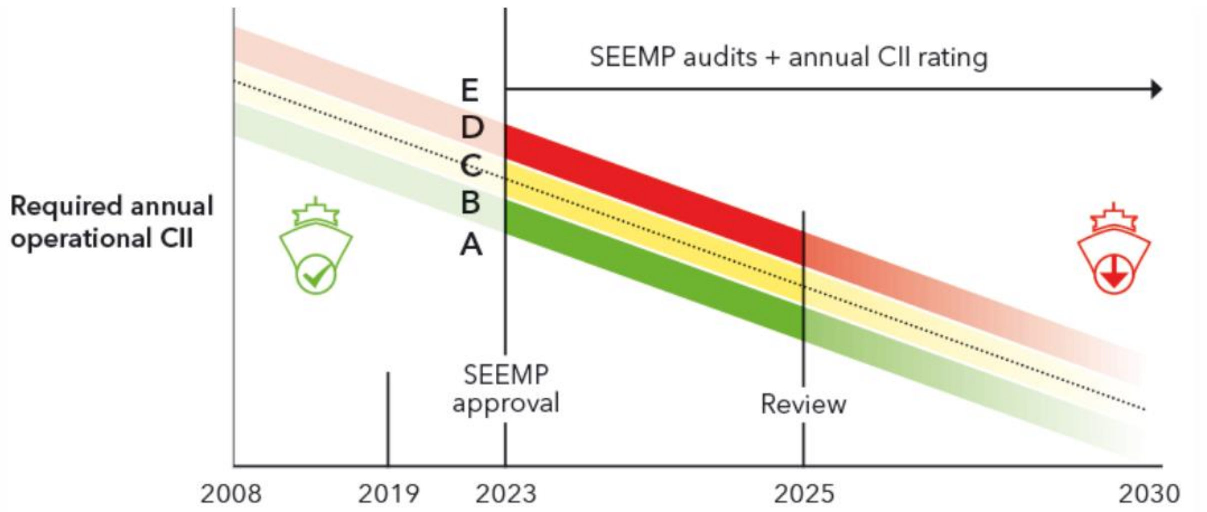

Fig.2: Required annual operational CII, CII - Carbon Intensity Indicator - DNV

The attained annual operational CII (Grams CO_2 per cargo capacity and nautical mile) and the related environmental rating (A to E), MEPC 354 78 (imo.org), will be noted on the DCS Statement of Compliance (SoC) and must be kept on board for five years and must be kept on board for a compulsory five years. Poorly rated vessels, this includes a D-rating for three consecutive years, or a one-time E-rating will result in the submission of a corrective action plan before the SoC can be issued. The corrective action plan should consist of an analysis of why the required CII was not achieved and include a revised implementation plan.

3. CII – Carbon Intensity Indicator, Correction Factors and Voyage Adjustments

The formula for calculating the attained CII was extended within the framework of MEPC 35 (78) incorporating correction factors and voyage adjustments. This means that for certain ship types and operations a "correction" to the CII may be given, either by removing a certain period of the vessels operation or by reducing the CII according to criteria explained below. Required annual operational CII, MEPC 354 78 (imo.org):

$$CII_{Ship} \triangleq \frac{\Sigma\, CF_j \cdot \{FC_j - (FC_{voyage,j} + TF_j + (0.75 - 0.03_{yi}) \cdot (FC_{electrical,j} + FC_{boiler,j} + FC_{others,j}))\}}{fi \cdot fm \cdot fc \cdot fi_{vse} \cdot Capacity \cdot (D_t - D_x)} \quad (1)$$

The motivation for introducing these corrections in the CII calculation mainly relates to the exclusion of competitive disadvantages due to energy-intensive cargo, special, energy-intensive ship operation due to short routes and cargo handling exclusively using onboard energy supply (e.g. generators and boilers). The corrections applied in the formula above can be divided into three sections:

a. Voyage Adjustments – $FC_{Voyage,j}$:
   - Securing the safety of a ship or saving life at sea (applicable for all vessels)
   - Sailing in ice conditions (applicable for ice-classed vessels)

b. Correction Factors:
   - $AF_{TankerSTS}$ – oil tankers engaged in STS voyages
   - $AF_{TankerShuttle}$ – shuttle tankers equipped with dynamic positioning
   - $FC_{electrical}$ – cargo-related electrical consumers (reefers, refrigeration plants, el. pumps)
   - FC_{boiler} – cargo-related fuel mass for boilers (heating, steam pumps)
   - FC_{others} – fuel mass for e.g. for pumps driven by combustion engines

c. Correction factors adopted from EEDI and EEXI calculation:
   - fi – capacity correction factor for ice-classed ships
   - fm – ships having ice classes IA Super and IA
   - fc – cubic capacity correction factors for chemical tankers
   - fi,VSE – correction factor for ship-specific voluntary structural enhancement

While the items mentioned under a. result from environmental and weather conditions, section c. considers exclusively fix factors derived from the EEDI/EEXI calculation considering the design characteristics of the ship. The subsequent consideration shall focus on the correction factors mentioned under c. $FC_{electrical}$, FC_{boiler}, and FC_{others}.

The IMO assumes that the total fuel quantity of the ship is recorded for the calculation of the CII. This includes main engines, auxiliary engines, gas turbines, boilers and for each type of fuel oil consumed, regardless of whether a ship is sailing or at anchor. For the collection of consumption data itself, different methods are specified:

a. Bunker delivery note (BDN)
b. Bunker fuel oil monitoring
c. Flow meters (according to vessels data collection plan)
d. LNG / alternative fuel tank monitoring

The determination of the CII based on a. - bunker delivery note only, although satisfying the basic requirements, is the least sophisticated method, on the one hand due to inaccuracies of the bunker procedure itself, on the other hand this method does not allow to focus on fuel oil consumption on a certain leg of a route and the aforementioned CII correction factors can only be taken into account to a very limited extent. At present, a substitute value for energy consumption is only envisaged for refrigerated containers if these are operated with on-board energy. Otherwise, it is crucial to install suitable and reliable measuring systems and sensors for automated data acquisition and storage in order to differentiate between the various energy consumers on board being able to deduct cargo related energy from the CII-calculation. Examples include the energy-intensive transport of liquefied gases due to the cooling and liquefaction plants installed on board. Tankers, especially heavy oil tankers, can deduct energy required for cargo heating and transport, e.g. for steam-driven pumps, from the CII calculation. Additional electrical consumers related to cargo handling may be calculated with an approximation of the Specific Fuel Consumption. SFOC in g/kWh associated with the relevant source of electrical power as per the EEDI/EEXI Technical File or NOx Technical File. In the case of ships without a Technical File, a default value of 175 g/kWh for 2 stroke engines and 200 g/kWh for 4 stroke engines shall be applied.

4. Market impact - vessels affected

The CII rating in general will in future affect ship owner and charterer in the same manner, not least impending penalties and rising fuel prices will force and motivate to monitor and optimize the vessels operation. Focussing on IMO´s approach to deducting cargo-related energy consumption a 36% share could benefit from applying that. The potential reduction strongly depends on the respective operating profile of the ship and the cargo to be transported. The greatest saving is considered on gas tankers, trading on short distances, due to extensive energy consumption for required pressure reduction during the first days on sailing after loading the vessel.

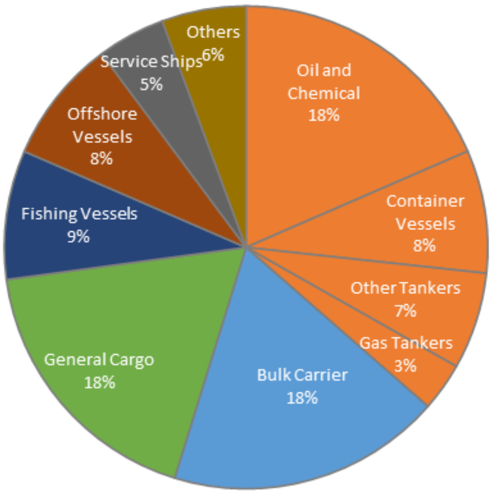

Fig.3: World Merchant Fleet Distribution, equasis.org

5. Technical Requirements for On-board Energy Monitoring

As already stated in chapter 3, the IMO authorises the vessel operator within the regulatory framework of SEEMP Part II to submit a vessels Data Collection Plan, in which is specifies how individual energy mass flows relevant for CII calculation in the form of fuel or electrical power shall be monitored and recorded, MEPC 346 78 (imo.org). Also self-diagnostic algorithms, maintenance and device-calibration intervals must be defined within this document.

The system itself must consist of at least of an iPC for data acquisition, fuel flow meters for main engine, auxiliary engine and boiler as well as electric power meters for generator and cargo related switchboards, e.g. for reefer containers or handling/conditioning units on oil or gas tankers. Navigation data (vessels position, speed, rudder angle, wind speed, etc.) can be read out and transmitted from the wheelhouse via interface.

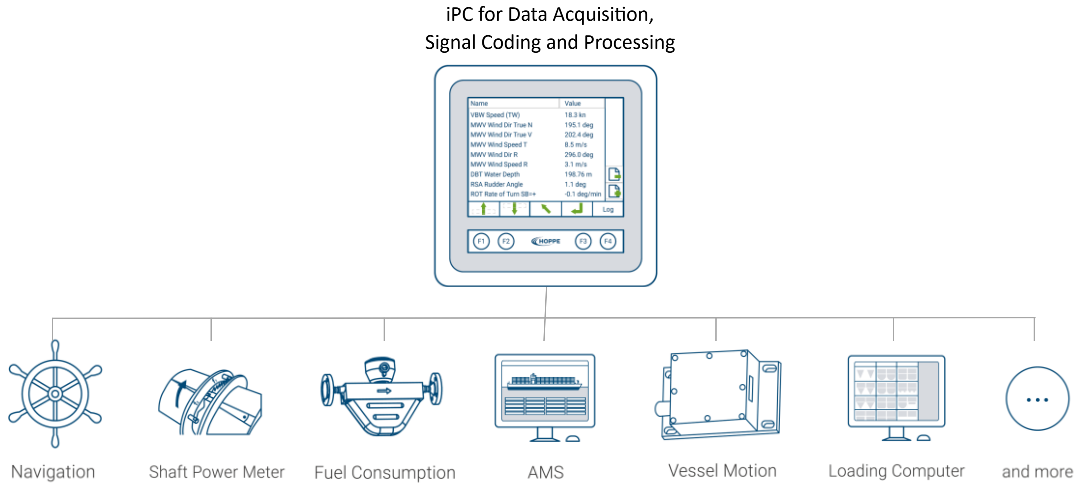

Fig.4: System Requirements for CII-related energy data acquisition and vessel optimization

Optionally, the system can also be equipped with further components such as draught measurement (dynamic trim), shaft power meter (plausibility check of the fuel consumption of the main engines depending on the engine condition or hull condition), loading computer, etc., which enhance the database in its capability as instrument for holistic ship optimisation.

6. Added Value trough digitalisation and MIoT©

The connection of a Vessels Performance Monitoring System – even if only focused on CII-relevant data - is predestined for digital connection technologies, not least to generate transparency of the vessels status on both, crews and owners / ship operators perspective. Hand in hand, ship and fleet operations can be sustainably optimised from an operational and strategic point of view in terms of costs and greenhouse gas emissions.

- **Ship to Shore infrastructure:** A vessel performance monitoring system in its function as a data logger or IoT device offers the possibility to build a proper (stable, low bandwidth, cyber-secure, etc.) ship-to-shore infrastructure. It will be possible to monitor all essential parameters of the performance monitoring system and connect additional data sources without major effort. With the data collected and stored in the cloud, it will be possible to analyze and evaluate the data over a long period of time. With the high-quality data stored over a long period of time, it is in turn possible to improve the performance of the vessel and investigate minor and major issues.

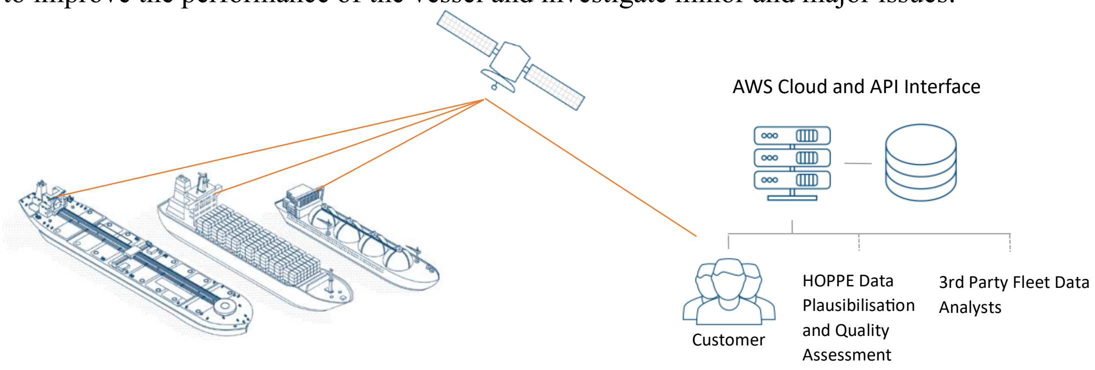

Fig.5: Ship to Shore Data Highway

- **Data sharing and collaboration:** Modern cloud solutions allow easy integration between suppliers, ship-owners, charters etc. Web Application programming interfaces (APIs) have been adopted within the industry. Testing and identifying the benefit of a new application on a set of high-quality high-frequency data has never been as easy as it is today. Decision support tools for hull-cleaning, weather routing, engine maintenance are much easier to integrate nowadays. Barriers for collaboration can be reduced and time for integration is lowered.

- **Remote Updates and support:** With the establishment of a permanent ship-to-shore connection remote updates and services will be available. A reduction of service attendances and improvement of mean time to recovery has been identified within remote-enabled systems within Hoppe products. In additional travel requirements are reduced, helping to reduce the general carbon footprint. Future outlook: Integration of self-diagnostic algorithms to empower the system avoiding downtimes by forwarding health data to crew and ship management (predictive maintenance).

7. Conclusion

The decarbonisation targets set by the IMO for the reduction of greenhouse gases are progressing rapidly, as can be seen from the conclusions of the 80th MEPC meeting in early July 2023. The resulting measures concern both the short-term optimisation of ship operations and the long-term technical design of ships, propulsion units and energy resources used.

With the mandatory introduction of CII monitoring based on fuel consumption data, the acquisition of the energy demand of the individual consumers on board the ship is at least mandatory when considering deductible energy expenditures caused by cargo handling and thermal conditioning (cooling / heating) that can be deducted from over-all energy requirement of the vessel's operation.

The technical environment such as data acquisition / processing unit, sensors and interfaces to the offers even more - namely the data basis for a holistic optimisation of the ship's operation and, last but not least, increases transparency for efficiency and health state of the vessel's technical infrastructure. As a result, a sustainable and cost-efficient fleet operation can be realized with these Performance Monitoring Systems in a straightforward way, with joint cooperation by digital connection between vessels technical management and crew.

References

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The Only Model You Need for Data-Driven Vessel Modelling

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Abstract

Precise modelling of vessels' dynamic behaviour based on high-frequency data is more crucial than ever in the shipping industry. Data-driven and deep learning techniques are increasingly popular due to their impartial estimations of a vessel's dynamics and the reduced deployment time and effort compared to traditional methods. However, purely data-driven methods can face data scarcity and may not perform equally well under different conditions. One approach to solving these problems is transfer learning, where a similar vessel is used to assist in the learning process of a target vessel with fewer or incomplete data. Although transfer learning is a proven approach, it can be challenging to implement in practical settings as it requires a careful selection of a similar vessel's model to be used in the adaptation phase. In this study, we introduce a novel method that eliminates the need to match sister vessel models with target vessels in transfer learning scenarios. Using a representation learning approach, we train a single model in a multiple-vessel dataset with the aim to capture and disentangle the dynamics of any vessel type while still being flexible enough to match and adapt to the available data of any target vessel. We demonstrate empirically that this single model can comprehend the dynamics of any vessel type, including their response to any weather condition while remaining adaptable using only a small amount of data, thereby completely solving the problem of matching models between vessels in transfer learning settings.

1. Introduction

The field of Machine Learning (ML) and Artificial Intelligence (AI) has witnessed astounding progress, thanks to many independent factors including algorithmic improvements, big data availability, and computing power increases. These advancements keep redefining the state-of-the-art (SOTA) making ML and AI the go-to solution for addressing critical challenges across diverse domains. Notably, domains such as computer vision, *Krizhevsky et al. (2012)*, speech recognition, *Hinton et al. (2012)*, natural language processing, *Mikolov et al. (2013)*, and bioinformatics, *Alipanahi et al. (2015), Zhou and Troyanskaya (2015), Ramsundar et al. (2015)*, have benefited significantly from these breakthroughs. In the past year, the successes of generative AI, including image synthesis from textual description, *Ramesh et al. (2021)*, and dialogue systems like ChatGPT seem to pave the way for another cycle of major ML innovation. However, the proliferation of practical production-level autonomous decision systems, including those found in finance, medicine, autonomous vehicles, and shipping, *Coraddu et al. (2019)*, poses high-stakes outcomes for their users.

Unlike traditional methods that heavily rely on expert prior knowledge and computationally intensive inference processes, ML methods prioritise offline training with ample computational resources. As datasets and computational resources continue to expand, the future of ML in the shipping domain appears promising. Although numerous ML methods exist, each with their own strengths and weaknesses, deep neural networks (DNNs) currently dominate the field, particularly for tasks involving vast amounts of unstructured data.

In recent years, interest for applications of machine learning in various aspects of the shipping industry has been steadily increasing, with a large and increasing number of scientific studies, *Coraddu et al. (2019), Papandreou and Ziakopoulos (2022), Tsompopoulou et al. (2022)*, as well as novel products and services being developed. Maybe the most widely researched problem in the subfield is power or fuel oil consumption (FOC) prediction, with approaches like *Jeon et al. (2018)*, who compare polynomial regression (PR), support vector machines (SVMs) and artificial neural networks (ANNs). *Levantis et al. (2020)* used Gaussian process regression correlating FOC with a product of speed through water and mean draft exponentials. Their model was trained on data from one vessel covering a year of operation and evaluated on operational data from the following year. *Papandreou and Ziakopoulos (2022)* found eXtreme Gradient Boosting models to outperform ANNs for the FOC of a very large crude oil carrier (VLCC). Other works, instead of focusing on single-vessel applications, have investigated using data from larger fleets for their models, such as *Wang et al. (2018)*, who used low frequency data from a container ship fleet and applied LASSO (Least Absolute Shrinkage and Selection Operator), Gaussian processes, support vector machines and neural networks. In a separate study, *Le et al. (2020)* harnessed operational data from a multitude of Korean container vessels and used an ANN to predict FOC for five distinct container ships of varying sizes, which they found to be more effective than regression models.

1.1. Transfer Learning and Representation Learning

There are two important aspects of ML that aim to improve modelling with limited data, transfer learning and representation learning. Each method tackles the learning problem at a different level and in this work, we leverage both as part of the same model training pipeline.

Representation learning is a fundamental aspect of machine learning that involves automatically discovering meaningful and informative representations or features from raw data. By leveraging deep learning, neural networks and other algorithms, representation learning aims to transform data into compact, hierarchical representations that capture salient patterns and features. Embeddings, a key component of representation learning, refer to the process of representing objects or entities as low-dimensional vectors in a continuous space. Embeddings capture the essential characteristics, semantic relationships, and contextual information of the objects, facilitating efficient computation and enabling tasks such as classification, recommendation, and information retrieval. Notable contributions in the field include word embeddings, *Mikolov et al. (2013)*, image embeddings, *Kiela and Bottou (2014)*, graph embeddings, *Dettmers et al. (2018)*, pretrained language models, *Devlin et al. (2018)*, and contrastive learning techniques like Siamese networks, *Bölücü et al. (2023)*.

Transfer learning is a powerful technique widely employed in ML. Instead of training a model from scratch on a specific task, transfer learning involves leveraging knowledge gained from training on a large and diverse dataset. By using a pre-trained model's learned features and representations, which capture general patterns and cues, the model can be fine-tuned on a smaller, domain-specific dataset. This approach enables the model to learn task-specific nuances more efficiently, even with limited labelled data.

One of the main limitations of such techniques when applied to vessel modelling is that the source vessel needs to match closely the characteristics of the target vessel so as to achieve optimal results. Although this is attainable when using a big model database to achieve a good match in terms of vessel’s characteristics, other limitations can also compromise the source model’s performance, e.g. it is possible for the operational conditions between the source and target vessels to not match, or the transferred model to be trained on a limited dataset.

1.2. Our approach

To alleviate these limitations, we propose a model architecture incorporating additional context inputs that describe the unique characteristics of each vessel (e.g. hull geometry). Such a model can be trained using large data from multiple vessels of any type, practically encompassing the entire available dataset. It facilitates zero-shot learning, enabling the model to generalise to new vessels by seamlessly interpolating the characteristics of previously encountered vessels in order to match the target vessel.

When confronted with vessel-specific data (even at scarcity), the model can still leverage the acquired knowledge from other vessels while being specialised to the specific vessel's distinct characteristics and hull state. This approach proves advantageous in scenarios where limited data availability hampers traditional modelling techniques.

The utilisation of a single, universal model eliminates the need for precise matching of pretrained models (i.e. of specific vessel types and operational conditions), facilitating a seamless transfer learning protocol. By jump-starting the model adaptation process, our approach expedites the practical application of machine learning in the shipping industry. Moreover, this approach brings additional benefits, including enhanced robustness and improved performance in generalising to diverse weather conditions, even unseen in the target vessel's own data.

2. Methodology

2.1. Regression

Let us consider the common scenario of predicting the power generated by a vessel's main engine, based on operational and weather conditions. Assume we have a dataset of input-output pairs available for model training, denoted as $D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_K, y_K)\}$, where each input x_i represents a vector that contains all the input features (speed, acceleration, wind, currents, draft etc.) and each output (or target) y_i represents the generated power at these conditions. This is a standard regression problem in ML. We use a neural network to represent the unknown function that estimates y_i from x_i. After successfully training the model on a suitable dataset of a vessel, the model should be capable of accurately predicting power across most, if not all, realistic operating conditions for the vessel at hand (vessel specific model).

The proposed model (vessel informed) is still regression-trained, but using data from multiple vessels. We achieve this by merging data from all vessels of all available types to train a single, universal hull model which takes additional data as input: the key vessel characteristics. Thus, a single model can explain multiple data distributions arising from different hull structures and operational conditions. The aim is to seamlessly specialise at inference-time to specific vessels without retraining. Note that the scope of this model is not to capture a vessel's state that could shift, e.g. due to fouling. Such aspects can only be handled during the adaptation phase using vessel specific data in a transfer learning setting.

Intuitively, the model, after going through a large dataset containing data from many vessels, learns how different aspects of a vessel's hull geometry, vessel type and other vessel characteristics, combined with operational and weather conditions, define the power consumed by the hull. This universal model "understands" the dynamics of different vessel types and can estimate the power consumption of unseen vessels. This modelling capability of generalising in previously unseen domains is referred to as zero-shot learning, *Socher et al. (2013)*, in the ML and AI literature.

2.2. Training, validation and testing

The usual process of training and evaluating such a model typically involves splitting the dataset into two or three parts: a majority portion for training, a portion for validation, and a portion for testing. Splitting the original dataset into training, validation and test sets is often as straightforward as randomly assigning every point in the original set to one of the three subsets, according to a preset probability distribution (e.g. 80% training, 10% validation, 10% testing).

However, in real-world scenarios, it is unlikely for the model to be tested on randomly selected data points. For example, it is more realistic for the test set to consist of the most recent part of the dataset (points collected closer to the present time), i.e. earlier data points being utilised for training and the model being expected to perform accurately on more recently collected data without retraining.

The above considerations have been taken into account for the transfer learning and adaptation experiment in Section 3.2, where we simulate the case of modelling vessels with transfer learning under limited operational data.

The training and evaluation protocol for the multi-vessel training is a folded cross-validation scheme (across vessels) and is explained in detail in Section 2.4.4.

2.3. Dataset construction

For a selected set of vessels, the minimum required number of data points for any vessel was set to a few days at 1,440 data points per day. A vessel type was considered eligible for inclusion in the vessel set only if it was represented by at least 5 vessels. These requirements left four vessel types available: Containers, Bulk Carriers, Oil Tankers and Chemical Tankers. The total number of vessels that were used in our experiments was 76. The distribution of the vessels of each type and the respective amount of per-minute data points are shown in Fig.1.

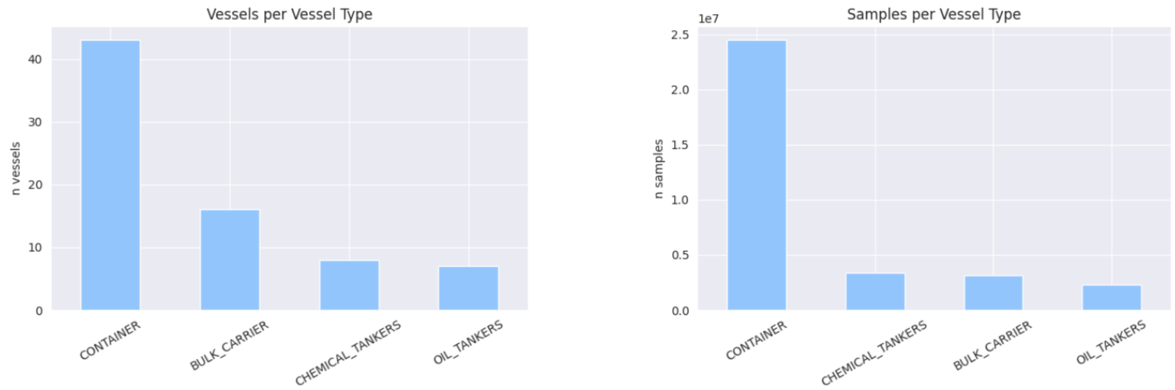

Fig.1: Makeup of dataset in terms of numbers of vessels of each vessel type (left) and numbers of data points coming from vessels of each vessel type (right). The average container ship has been collecting data for a longer period of time than the others, which combined with the larger number of container ships, causes them to provide the vast majority of the data.

2.4. Model Architecture

2.4.1 Vessel Specific Baseline Models

We first describe the architecture of a standard vessel-specific model which is trained on a vessel's own data. This is a typical regression DNN where the inputs are the operational per-minute data listed in Table I and the output is the propeller's shaft power. This DNN can be seen as an operational encoder network $z_{op} = h_{op}(x_{op})$ followed by a linear prediction head layer $y_{pred} = g(z_{op})$. In this case, for each vessel we train a model using exclusively data from the vessel at hand. The data points are split randomly into a training set (80%), a validation set (10%) and a test set (10%). This model will be referred to as the vessel specific baseline model of the vessel.

Fouling modelling is excluded throughout this work for all model types, in order to simplify the overall experimental design, as fouling is not only vessel-specific but also time-dependent.

Table I: Input features used to represent the operational condition of the vessel at each point in time

Speed (Over-Ground) [kn]
Drafts (aft and fore) [m]
Wind (apparent magnitude and angle) [kn] and [°]
Currents (magnitude and relative angle) [kn] and [°]

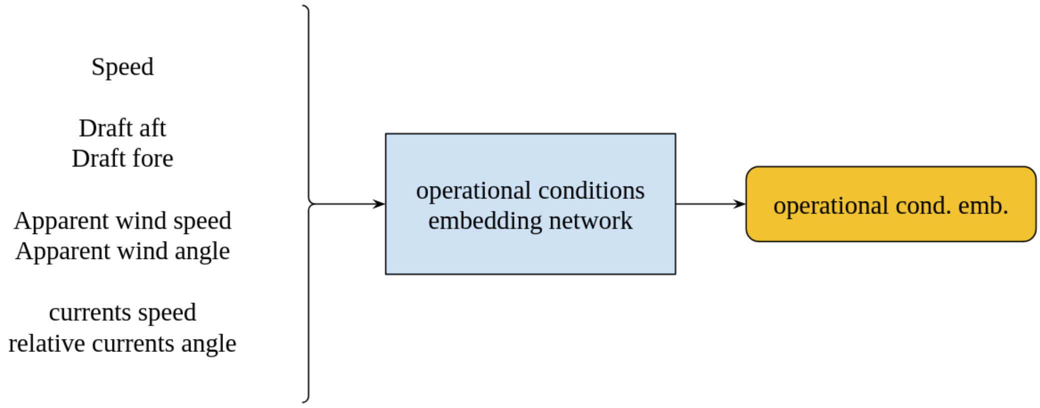

Fig.2: Architecture of the operational encoder network, used to obtain a vector embedding representing the operational conditions of the vessel at each point in time. The light blue square represents trainable neural network layers.

In the following subsections we describe the architecture of the vessel agnostic and vessel informed model both of which are trained on multi-vessel datasets.

2.4.2. Vessel Agnostic Model

The vessel agnostic model has the same architecture as the vessel specific baseline; but it is exposed to multiple vessel datasets. It serves the purpose of setting the performance of an "average" data-driven model. The vessel agnostic model has no way of knowing which vessel each data point comes from and thus can only provide a prediction for the "average" power across vessels and vessel types.

2.4.3. Vessel Informed Model (proposed)

In this paper, we propose the vessel informed model. This model combines the operational per-minute conditions with the vessel type and geometric characteristics of the vessel. The operational encoder part of the model is identical with the encoder h_{op} of the vessel specific baseline and vessel agnostic model.

In our approach, the vessel type and hull geometry features undergo an embedding process within a dedicated network, resulting in encoded representations as a series of real-valued vectors. This n-dimensional embedding space can be regarded as a learned encoding of the vessel's characteristics, whereby vessels with similar attributes should be positioned in close proximity, while significantly different vessels are situated further apart. The embedding network is trained jointly with the rest of the model, with the objective of minimising power prediction errors. By incorporating the vessel embedding component, our model effectively captures the intrinsic structure of vessel characteristics to facilitate accurate power predictions across vessels.

The network branch that encodes the vessel type is split into two sub-networks: the vessel type embedding network and the hull geometry embedding network. The first one is responsible for encoding the vessel type which is provided as a one-hot encoded vector x_{type} while the second one encodes the hull characteristics.

x_{type} is passed to the vessel type embedding network to obtain a vector $z_{type} = h_{type}(x_{type})$. The hull geometry embedding network encodes the geometric features x_{geo} of the vessel into another vector $z_{geo} = h_{geo}(x_{geo})$. These two encoded vectors are concatenated to form a single vessel embedding vector $z_{vessel} = z_{type} \oplus z_{geo} = h_{vessel}(x_{type}, x_{geo})$. The operational vector z_{op} is then concatenated with the vessel embedding z_{vessel} and passed through a fusion encoder in order to obtain the fused vector $z = h(z_{op} \oplus z_{vessel})$. A linear prediction head follows in order to emit the desired target predictions in the exact same way as in the previous models $y_{pred} = g(z)$. The described architecture of the vessel informed model encoder is shown in Fig.3.

All tested models have the same task of predicting the true shaft power at the current minute. The loss that is used is the mean squared error (MSE) between the true and the predicted value. The selected optimizer is Adam, *Kingma and Ba (2014)*, with a starting learning rate of 0.001. The learning rate is reduced after a few consecutive epochs of no drop in the validation error and the training is early-stopped if no improvement is seen on the validation loss after a set number of epochs. The batch size is set to a lower number when training the vessel specific baseline models (only one vessel) compared to when training the vessel agnostic and the vessel informed (multiple vessels) models. The reason behind this is to assure that in every batch we have sufficient representation of all vessel types, since the multi-vessel dataset is unbalanced across vessel types, with some types having a lot more data points than others.

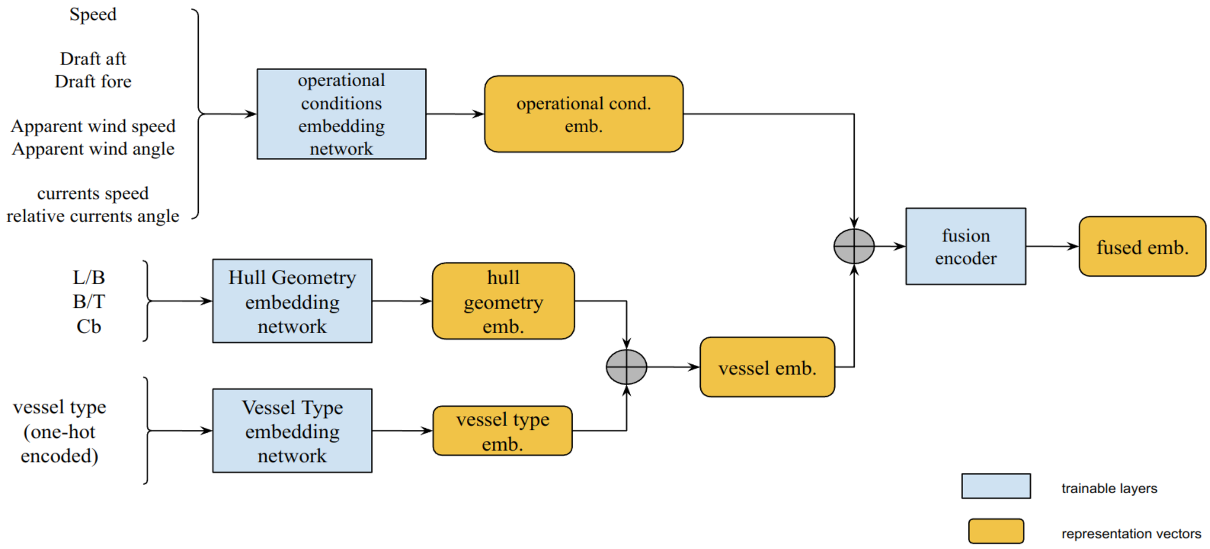

Fig.3: Architecture of the vessel informed model, used to extract information about the operational conditions of the vessel at each point in time, fused with information about the particulars of the vessel. The light blue squares represent trainable neural network layers, trained jointly and end-to-end with the downstream task, i.e. predicting power. L/B is the ratio of length between perpendiculars to extreme breadth underwater, B/T is the ratio extreme length underwater to mean draught and Cb is the block coefficient (ratio of underwater volume to the product of length between perpendiculars, extreme breadth underwater and mean draught).

2.4.4. Cross-Validation for Evaluation

In order to measure the generalisation error on unseen vessels, we use multiple vessels' data for training. We perform ten-fold cross validation following a different procedure. Instead of splitting randomly on the data points, we split on the vessels. Our entire vessel set is split sequentially into 80% of train vessels and 20% of inference vessels thus creating five different splits. The split is stratified on the vessel type meaning that the vessels' type distribution remains the same across the folds. Then, the inference set is further split into two equally sized sets, validation and test. Validation and test vessels are swapped to create an extra fold leading to a total of ten folds. The procedure is schematically depicted in Fig.4.

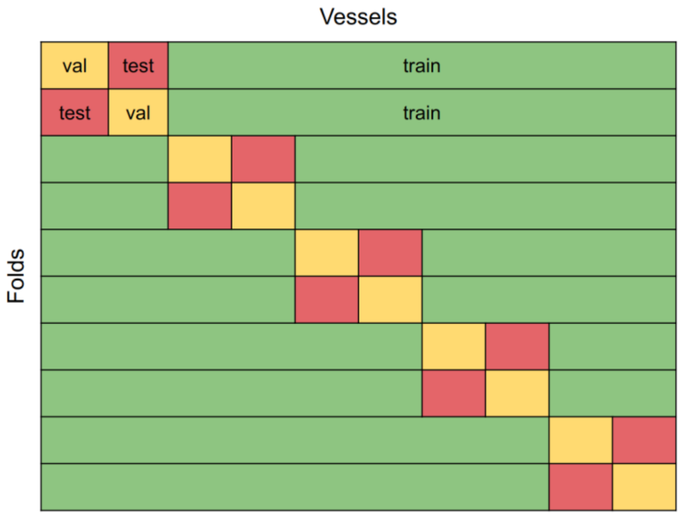

Fig.4: Illustration of the ten-fold cross-validation methodology. The vessels are divided into five folds (A, B, C, D, E) each subdivided into two sub-folds (i and ii). Each of the experiments reported in this paper is run by first training on B-E, validating on Ai and testing on Aii, then training on B-E, validating on Aii and testing on Ai, then training on A, C-E, validating on Bi and testing on Bii etc. Reported results are the average of all the sub-fold tests.

3. Experimental Results

3.1. Zero-Shot predictions

Zero-shot prediction refers to the ability of a model to make predictions on tasks for which it has not been trained, in this case to predict power on a vessel for which it has received no training data. It is impossible to accurately model the hull of a completely unseen vessel due to properties of the hull not captured by the geometry as well as those that change over time (e.g. due to fouling). To capture these, at least some data must be provided for the adaptation phase of a transfer learning protocol. Despite this, experiments with no training data can provide a good measure for assessing how suitable a model is for adaptation.

The performance of our vessel informed model is compared against three references. First, we train a vessel specific baseline model (the operational encoder model) using available data from the vessel in question. Second, we train the same operational model on data from all other vessels, without a representation of vessel characteristics (a vessel agnostic model). Finally, we use a model trained on only data from a sister vessel, which is the literature state-of-the-art approach when data for a vessel is not available. When a vessel u has no sister vessel in our database we detect the most similar vessel (nearest neighbour) using the learned vessel representations of the vessel informed model, to select the nearest vessel according to the Euclidean distance. After the vessel informed model is trained, we obtain a vector representation of each vessel by giving the encoder h_{vessel} the characteristics of the vessel as input: $z_{vessel} = h_{vessel}(x_{geo}, x_{hull})$. Thus, the nearest vessel v^* is the vessel of the training set whose embedding is nearest to the embedding of vessel u:

$$v^* = \text{argmin}_v\, d_{Eucl}(u, v).$$

Sister vessels are guaranteed to have a Euclidean distance of 0 between their embeddings, so this process always returns a sister vessel if one exists.

For the scope of this work, fouling modelling is not considered for simplicity.

Table II shows the Mean Average Percentage Error (MAPE), averaged across vessels. The vessel specific baseline has the lowest error as expected, as it is based on data from the vessel in question.

Despite being trained on much more data, the vessel agnostic model trained on all other vessels performs worse than the model trained on just a sister vessel, with the distortion due to differences between vessels outweighing the benefit of additional data. However, when the nearest neighbour is not a sister vessel the vessel agnostic model actually performs better.

The vessel informed model outperforms both the sister vessel model and the vessel agnostic model significantly, suggesting that it has successfully modelled the relationship between the vessel particulars and the current operational conditions, learning from other vessels without being distorted by their differences from the target vessel.

Table II: Mean Average Percentage Error (MAPE) of predicting the per-minute power of a vessel from its operational conditions using a model trained on data from the vessel (vessel specific baseline), compared to four methods trained only on data from other vessels: the same model architecture trained on other vessels (vessel agnostic), the same model architecture trained on the most similar other vessel which is not a sister vessel (nearest neighbour non-sister), the same model architecture trained on a sister vessel (sister vessel), and the vessel informed model (which also incorporates vessel characteristics) trained on other vessels.

	Power MAPE (%)
vessel specific baseline	9.55 +- 2.80
vessel agnostic	28.87 +- 18.80
nearest neighbour (non-sister)	29.21+- 23.56
sister vessel	21.47+- 11.78
vessel informed	**17.56** +- 6.44

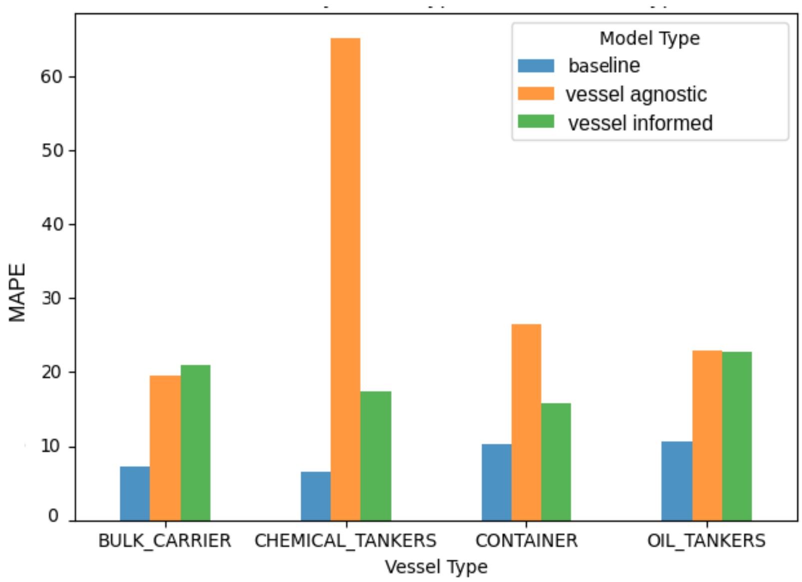

Fig.5: MAPE of predicting power for each vessel type of a model using only operational conditions trained on data from the vessel (blue), a model using only operational conditions trained on data from other vessels (orange) and a vessel informed model using operational conditions, vessel type and hull geometry trained on data from other vessels.

Fig.5 breaks the results down by vessel type. The vessel informed model performs well even for vessel types other than containers, which represent the vast majority of the data. The case of chemical tankers is particularly interesting. The vessel agnostic model failed completely (60%+ error), however the vessel informed model trained on the same mostly-container ship database was able to use its knowledge of the types and geometries of each vessel to provide reasonably accurate power predictions for each chemical tanker.

To verify how the vessel informed model is capturing vessel characteristics, we inspect the vessel embedding vectors i.e. the representation of the vessel characteristics learnt in training. To map the vectors to 2D space for visualisation we perform dimensionality reduction on a randomly selected fold using two algorithms, the non-linear t-SNE, *Van Der Maaten and Hinton (2008)* and the linear PCA *Jolliffe (2002)*. The results are shown in Fig.6. As expected, vessel type emerges as the dominant characteristic by which vessels cluster.

Fig.6: 2D visualisation of multidimensional vessel embeddings (left: t-SNE, right: PCA). Same coloured points represent vessels of the same type.

To qualitatively evaluate the performance of the models, we use them to perform Power-Speed (PV) simulations for each vessel. Every feature except for speed is fixed to a specific value as described in Table III.

Table III: Ranges and values of operational conditions used as inputs to models to generate PV curves. As currents are set to zero, speed over-ground is equivalent to speed-through-water.)

Speed (Over Ground)* [kn]	[min, max] of the vessel's data
Drafts (aft and fore) [m]	Mean value of the vessel's data
Wind (apparent magnitude and angle) [kn, °]	Varying along with speed to match 0 magnitude and angle of true wind speed
Currents (magnitude and relative angle) [kn, °]	Set to 0

Table IV: Legend of the colours used in the PV curves, Figs.7-9

Colour	Model Type
Blue	*vessel specific baseline* (operational model trained on data from vessel)
Orange	*vessel agnostic* (operational model trained on data from other vessels)
Green	*vessel informed* (model trained on data from other vessels taking into account both operational data and vessel particulars)

For the vessel informed model, the vessel characteristics are attached (and kept fixed) to the simulated data points in order for the model to be able to perform inference. Since many vessels (76 in total) were used in the experiments, we show six representative examples.

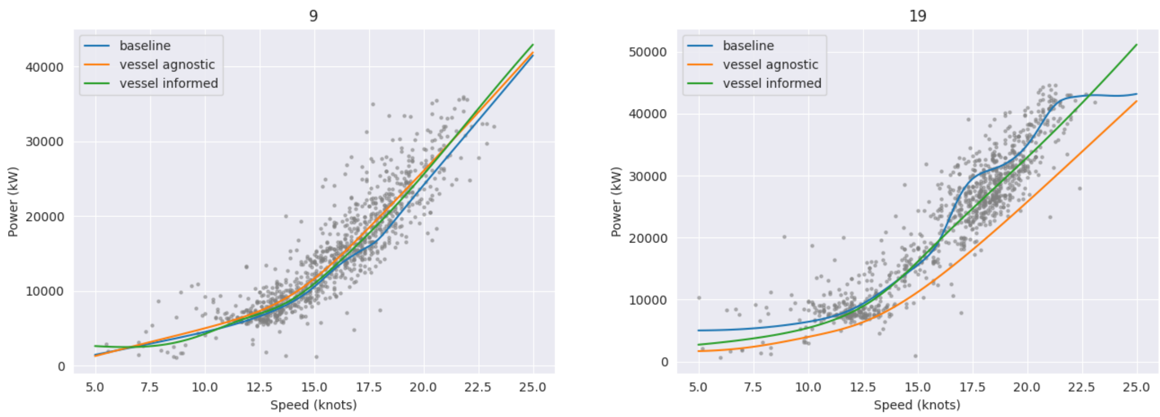

Fig.7: Power vs. Speed for two representative Container ships (left and right) showing actual data (grey dots) and predictions of a vessel specific baseline model trained on the actual data (blue) and vessel agnostic (orange) and vessel informed (green) models trained on other vessels

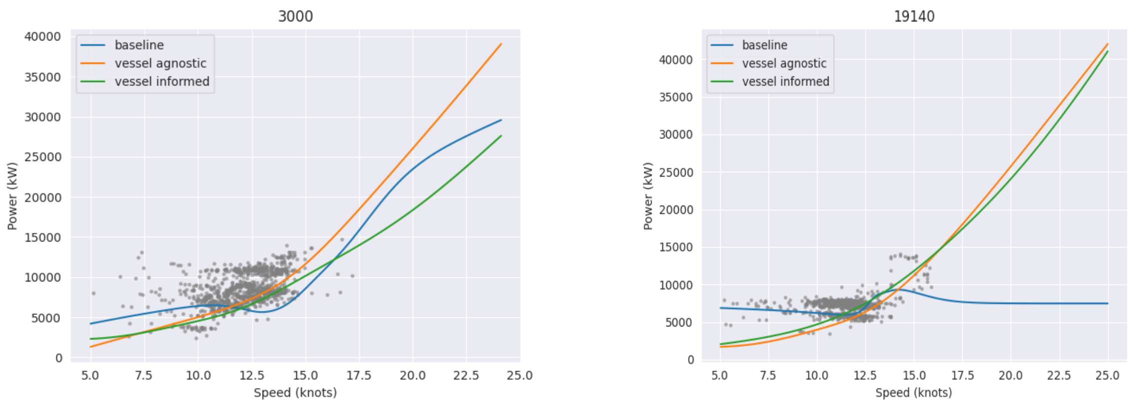

Fig.8: As Fig.7 for two representative Bulkers carriers (left and right)

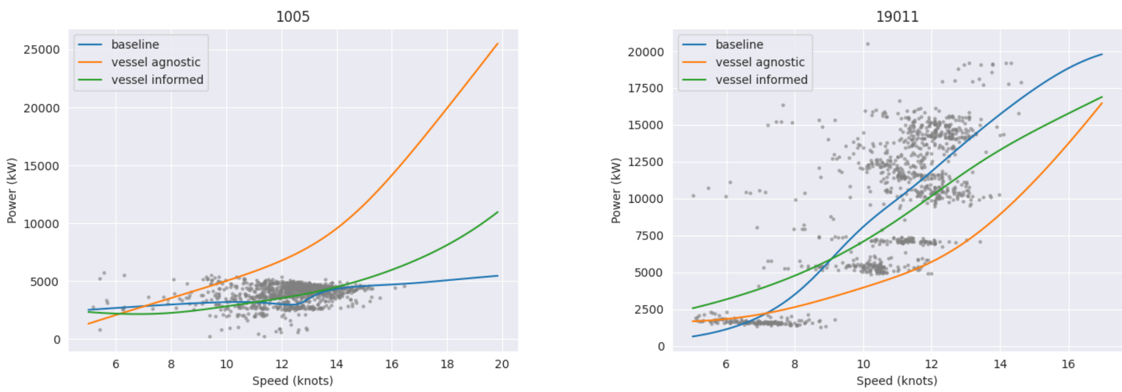

Fig.9: As Fig.7 for two representative tankers (left and right)

Interestingly, the vessel-specific models that achieve lower prediction errors often produce simulations that differ from the expected cubic relationship between power and speed. This is most likely a case of overfitting: the model has learned to fit the data to high precision, but inadvertently has also modelled noise and/or dataset biases. On the other hand, the vessel agnostic models underfit, deviating systematically from the data.

The vessel informed model more closely fits the data than the vessel agnostic model and is smoother and more robust than the vessel specific model. It seems to tackle the problem of limited operational conditions in some of the datasets (e.g. vessel 3000 and 1005), whereby even a dataset which large amounts of data points can turn out to have been exposed to a limited range of operational conditions e.g. weather conditions and speed, creating gaps which the vessel-informed models can fill in by using insights from other vessels.

3.2. Transfer learning and adaptation

In this experiment, we artificially limit the available samples and train our models by incrementally increasing the amount of data. Each vessel is limited to 12 weeks of data with a per-minute sampling rate i.e. 120,960data points. The first 10 weeks are used as training data, the last week is held out as a test set and the penultimate week is held out as a validation set. We start with the first week of available data and incrementally add a week at each step, training from scratch a vessel specific baseline model and adapting the vessel agnostic and vessel informed models whose training vessels' set did not include the target vessel. During the adaptation of the vessel informed models, the vessel encoder, which consists of h_{geo} and h_{type}, is held frozen. Only the operational encoder h_{op}, the fusion encoder, h and the prediction head, g are fine-tuned.

We plot the median MAPE across the vessels along with the interquartile range (IQR). Interestingly, the vessel agnostic model outperforms the vessel specific baseline, as at these small amounts of data, the latter's lack of data outweighs the former's lack of relevance. The vessel informed model outperforms both other models, combining the best of both worlds.

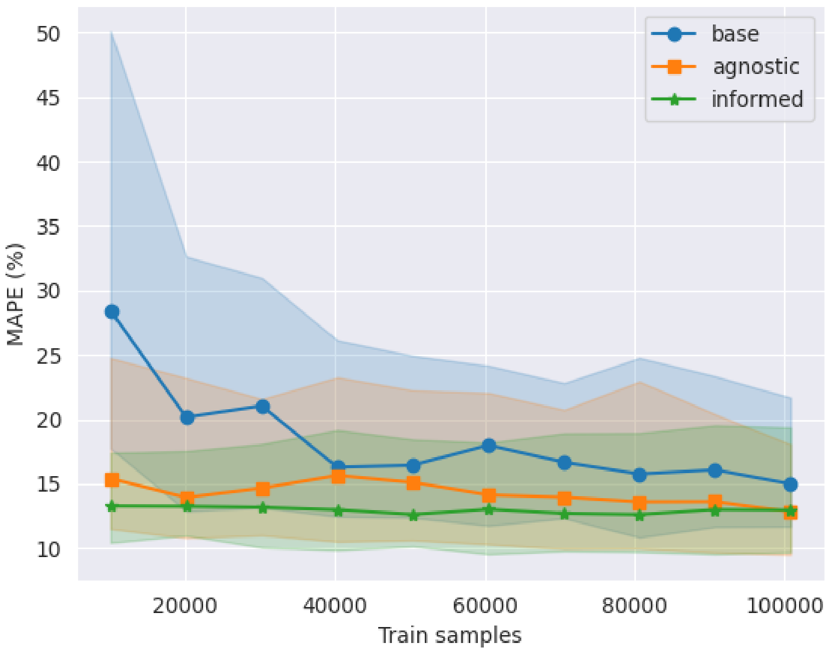

Fig.10: Performance (MAPE and IQR) when different numbers of 1-minute train samples of data are available from a vessel, at predicting the vessel's power: i. from its operational conditions using a model trained on the samples (base) ii. from its operational conditions using the same model architecture trained on the samples plus data from other vessels (agnostic), and iii. from its operational conditions, vessel type and hull geometry, using the vessel informed model trained on data from other vessels and adapted using the samples (informed). Each step of 10K samples corresponds to roughly seven days of operational data.

As expected, the fewer the available data points for a vessel, the more difficult it becomes for a vessel specific model to properly capture the vessel dynamics across a variety of conditions. Our proposed solution exploits learning from multiple vessels while simultaneously adapting to vessel-specific characteristics. This essentially allows the model to combine rich and diverse operational conditions into a common representation hence increasing the robustness and extrapolation performance.

4. Conclusions

This paper investigated the problem of predicting per-minute power of a vessel by leveraging data from other vessels and knowledge of vessel characteristics, both in conditions of no training data available from the vessel and in conditions of limited training data.

In conditions of no training data, the literature state-of-the-art is a model trained on a sister vessel, if one is available. Simply training a vessel agnostic power prediction model on data from large numbers of other vessels was confirmed to perform worse at predicting power than training the same model on just data from a sister vessel. This is to be expected as vessels with different characteristics require significantly different amounts of power in similar operating conditions. However, using our proposed architecture to enable the model to learn how hull geometry and type inform power from multiple vessels, we were able to demonstrate considerably better performance than the sister vessel model. Further, performance of our vessel informed model remains strong even when the majority of vessels in the dataset are of a different type.

While predictions made by the vessel informed model using only data from other vessels and the vessel particulars are not as accurate as those made by a model trained on actual data from the vessel, the vessel informed model does have advantages over the vessel specific model, in particular when making predictions in conditions where data is not available, as illustrated in the P-V curves.

In the limited training data conditions, we showed that by leveraging data from other vessels with knowledge of each vessel's particulars, the vessel informed model trained on both the available data from the vessel in question and data from other vessels can achieve considerable gains over models trained only on the vessel in question. The vessel informed model achieves high levels of accuracy even with small amounts of data (< 2 weeks sailed) from the new vessel, with the advantage it gives over other models increasing the smaller the amount of available data.

Data-driven methods have significant advantages for vessel performance modelling, but there will always be vessels with limited or biased datasets, such as newly constructed vessels, vessels with newly installed sensors, and those that have undergone retrofits substantially altering their performance. Combining representation learning with transfer learning can alleviate both the problem of vessel matching and robustify the training procedure, especially when data availability is low. In this study we proposed a methodology to construct DNN models that can effectively leverage large datasets, collected from a large number of vessels with different types, with the ability to perform zero-shot prediction for unseen vessels. This capability is achieved through modelling the impact of different vessel characteristics in the power consumption. Notably, this is accomplished without relying on analytical approximations, but by properly ingesting an extensive array of vessels with varying geometries and vessel types.

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Improving the EEXI by In-Service Speed Trials

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Abstract

This paper describes the procedures in performing in-service speed trial analyses by the IMO MEPC 1/ Circ. 901 for the purpose of EEXI calculations. The guidelines outline how speed power relations can be established as an alternative for the cases where design information is missing and the EEXI has to be estimated by statistical calculations. The speed trial location and time is flexible since the trial data is analysed with data from a real time performance system and is remotely monitored by a Class representative. The paper includes two case studies where vessels have performed the in-service speed trials and the result of these are benchmarked to other available results. The in-service speed trials show promising results and can be used as an alternative to model tests and CFD simulations.

1. Introduction

As part of the short-term measures to reduce the CO2 emissions from Shipping, IMO introduced the EEXI as a measure to enter into force by 1st January 2023. As the design of new build vessels had the attained EEDI, existing vessel also were set up in a scheme where the design measures for the ship had to fall into specific boundaries for the CO2 emissions. If a vessel would fail to comply, measures should be implemented that would improve the EEXI. Measures most relevant for existing vessels could be:

1. retrofitting devices or measures that could improve the energy efficiency.
2. reducing the power of the main engine (with Engine Power Limitation = EPL)
3. A combination of 1 and 2

Any of the effects of including the measures would then be used in the calculations for the "new" EEXI which then would be approved by the verifier which in this case is a Classification Society (Class).

2. Calculating the EEXI

To calculate the EEXI a number of design information should be available. The calculation procedures are described in *IMO Res MEPC 350.78* and to complement this IACS has issued a set of guidelines for the calculations, *IACS No. 172 EEXI Implementation Guidelines*. The most critical documents in the calculations are the speed trial documents and the engine fuel consumption information.

To match the required EEXI for a vessel, the attained EEXI is adjusted by adjusting the V_{ref} and the main engine power. The calculations lead to a new V_{ref} and a resulting limited maximum main engine power (MCRlim) which then defines the EPL. The EPL can be overrideable, which means that if the vessels should need additional power e.g. in case of an emergency, the EPL can be broken and the vessel would have the full power available. The EPL can also be non-overrideable which means the vessels EPL is fixed and cannot be broken.

In the guidelines from IACS there are guidance notes on the procedures for how the speed trials were to be held and from which documents the fuel oil consumption values should be established. For older vessels the information might not be available for the owner or the procedures on how the information has been collected might not meet the demands. For vessels where this has been the case, a set of statistical calculations has then been derived. Mainly to get a V_{ref} which normally would come from the speed/power curve from speed trials and to get the engine(s) SFOCs which normally would come from the factory acceptance tests (FAT). Specifically, for the V_{ref}, the usage of the statistical value can be unfortunate since it would not very often describe actual performance of the vessel and in many cases penalize the vessel on its EEXI.

If sea trial or tank test has not been conducted, the following approximation can be applied:

$$V_{ref,app} = V_{ref,avg} - 2\sigma \; [knot]$$

Where $V_{ref,avg}$ is a statistical mean of distribution of ship speed in given ship type and ship size, to be calculated in accordance with the guidelines developed by the Organization, based on IHS Seaweb database and σ is a standard deviation of distribution of ship speed in given ship type and ship size, to be calculated in accordance with the guidelines developed by the Organization, based on IHS Seaweb database.

Statistically, Vref,app refers to the worst 2.5% performer in terms of ship speed based on IHS Seaweb database. Therefore, this approximation will secure the EEXI value not overestimating the ship's energy efficiency performance. A couple of examples (for bulkers and tankers) can be seen in Fig.1.

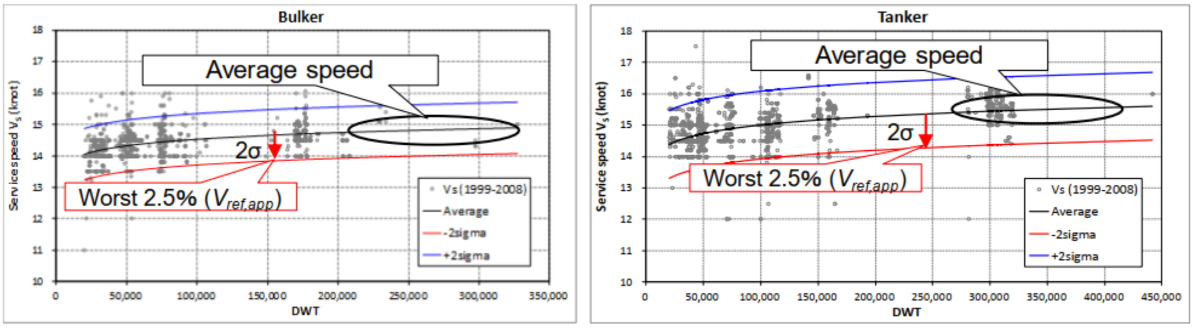

Fig.1: Estimation of Vref for Bulkers and Tankers

In addition, to the knowledge of the IHS Fairplay being inaccurate in its vessel information, the refence values would in all be unfair to use for well performing vessels, where the available design information is inadequate for an EEXI calculation.

3. The IMO MEPC1./Circ 901

If not using the statistical measures, shipowners then have had the option to have a new speed trial done. A traditional speed trial would include a model test / CFD simulation and a speed trial at a reference condition to get to the EEXI speed-power curve for finding the V_{ref}. Further the trial should be attended by Class and the whole arrangement would be costly and difficult to fit in to a busy schedule for vessel operating in a busy market.

Over the last years more vessels have been using performance monitoring systems from different of providers and basically, the vessels performance is monitored continuously under operation by the vessel sending data to shore where it is analyzed in a software system available from the chosen provider. The frequency of which the data is sent varies pending on the chosen system, where a system with a high updating frequency has the advantage of being more accurate and faster in detecting any performance issues. These systems are being used in general to monitor hull/propeller/engine performance, to evaluate performance of antifouling paints, retrofits of Energy Saving Devices and in general to establish new baselines after a drydock or when acquiring new (used) vessels.

With the above in mind, the idea of introducing a more efficient way to conduct a speed trial without taking the vessel out of service, the BIMCO organisation called for a meeting with stakeholders in the industry that could have knowledge and interest in working towards a solution that would include in-service measurements, remote monitoring and a flexible means to perform speed trials that would fit in to a busy vessels schedule.

A group of experts defined the scope of work and after the first draft versions of the procedures were issued, RINA and Japan were engaged in the work and the Circular was presented in IMO at the MEPC 76 and the final version was approved at the MEPC 78 as MEPC.1/Circ. 901.

3.1. What is new in the circular?

In general, there are a lot of references to recommended speed trial practices, mostly to the ISO 15016:2015 standard and this makes sense to ensure procedures and methods are uniform for the different stakeholders involved in the trial. The following differs from what has been the standard for these trials.

- If a vessel does not have any model tests or speed trials at or around the EEXI condition, a speed trial can be performed at a reference condition. This condition is defined as the condition to where it had a speed trial when it was new. After the speed trial, the two speed power curves are compared, and the result is used for reference for the verification of the trial. Then the vessel can in addition perform a second speed trial at the EEXI condition. The result of this speed trial is then used in the estimation of the V_{ref} for the EEXI calculations.
- A speed trial does not have to be attended by a Class representative on board the vessel. If a vessel has a performance monitoring system with high frequency data updates that can be accessed by Class during the speed trial, the attendance can be done remotely. There are further no restrictions to where the speed trial can be held as long as it is held within the framework described in the circular.
- It is the Shipowners responsibility to execute the speed trials according to the procedures in the circular. In the planning phase it is further recommended to include Class representatives for them to be aware and prepare for the trial and familiarize themselves to the performance monitoring system used during the trial.
- The main engine fuel oil consumption during the speed trials is included as a measure. This for the Shipowner to include the consumption information for a vessel baseline for future use and for the verifiers to use as a sanity check on the speed – power curves produced from the trial.

The circular includes very practical measures and checklists for equipment that should be included in the analysis. This makes it easier for the participants to plan and execute the trials. It further ensures transparency of the methods used and is helpful in the discussions with Class representatives in the preparations of the trials.

The following two case studies describe the execution of speed trials for 2 different vessels, where the trials were held with the intent of improving the EEXI for vessels.

4. Case Study vessels

The first case vessel had the following issues with regards to the EEXI:

- The vessel was delivered in 2008.
- The vessel is overpowered and designed for a specific operational profile that do not match the current profile.
- The EPL needed to meet the required EEXI were assumed too high for the vessel to be flexible to meet the needed speed to continue working in the current pool.

- There was no delivery speed trial information that matched the requirements to be used in the calculations.
- There was a copy of a sister vessels model test but since the owner had applied Energy Saving Technologies to the vessel just after a drydock, it was considered that a speed trial in the reference condition should be tested to verify the improvement to the speed power curve.

The second case vessel had the following issues with regards to the EEXI:

- The vessel was delivered in 2008.
- The vessel is overpowered and designed for a specific operational profile that do not match the current profile.
- The EPL needed to meet the required EEXI were assumed too high for the vessel to stay in the trade that it was currently operating in.
- There was no delivery speed trial information that matched the requirements to be used in the calculations and all calculations had to be done by statistical means.

For both cases, it was therefore decided that a speed trial should be held just after drydocks in 2023. Class was included in the preparations and a remote survey team was introduced to the procedures and the performance software that was going to be used in the trial.

4.1. Performance data

Both vessels have during dry dock been fitted with fuel flow meters and a shaft torque meter. Both sets of equipment were tested and calibrated before use and the certificates were available for the verifiers. Further, all relevant performance data was logged through a performance system with a high frequency data update, and it was available during the speed trial assessment on board and ashore.

The data was logged with high frequency according to the recommendations described in the MEPC.1/Circ. 901.

During the trial, the progress was to be monitored online by verifiers and the office team. The performance system was set up with the relevant parameters for an online overview. Time series were extracted after the vessel was in steady state condition after each power setting, see example in Fig.2.

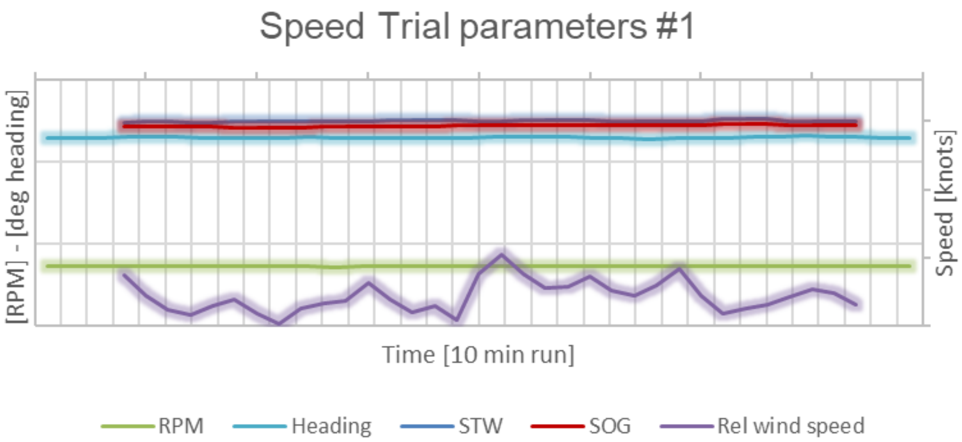

Fig.2: Sample performance data

4.2. Performance model

A digital twin model was developed for the vessels. Based on the available design information, a model including design, equipment, consumers and propulsion characteristics was developed for the purpose of the performance analysis and to set boundaries for the data measured on board. The model was included in the software for the speed trial analysis and the measured data was validated up against model values. Since the model represents the performance of the vessel when it was new, it is in this case used as the baseline for propulsion and consumption. The delta or the offset from the new model is then derived based on the speed trial analysis and gives an indication of the degradation of performance over the years it has been in operation. The delta is then used to update the model and set a" new" baseline for future performance monitoring and analysis.

4.3. Trial sites and conditions

The trial sites were chosen while the vessel was underway. The weather forecast was studied, and suitable areas were chosen and where conditions were within the boundaries of the described conditions in the MEPC.1/Circ. 901. Further the trials were held in daylight and in areas with little or no traffic.

Environmental conditions were measured on the actual trial site, see example in Table I. The wind was measured by the anemometer in the ships and the sea state was estimated by visual observations, see example Fig.3. The effect of currents was considered by using the mean of means method in the speed trial analysis.

Table I: Environmental conditions data sample

Water depth	132 m
Air temperature	12.3° C
Sea water temperature	16° C
Sea water density	1.025 t/m^3
Anemometer height	36 m

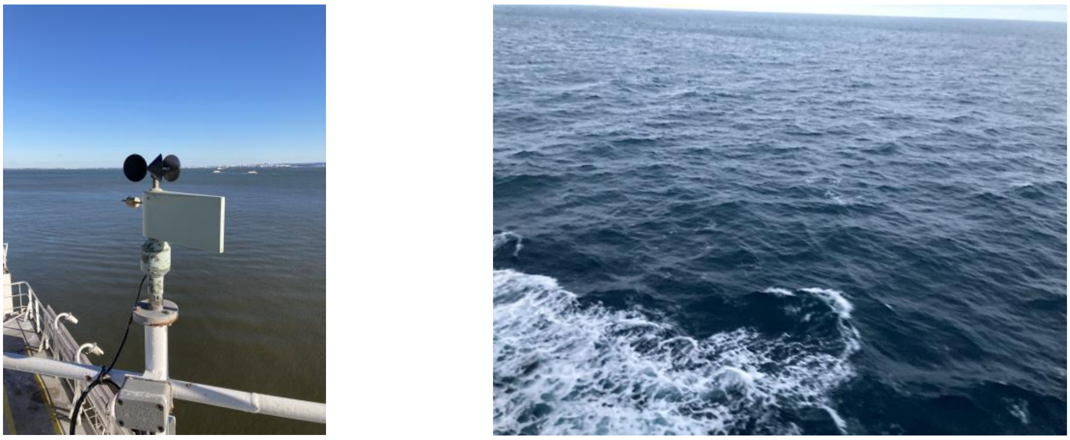

Fig.3: Wind and wave estimations

Trials were held at 4 different engine loads where the focus was on loads from 35 to 90 % of MCR, where the load range matched the operational profile of the vessel. Fuel specifications were obtained from the bunker delivery note and used in the ISO corrections of the SFOC, see samples in Table II.

Table II: Fuel specs and load settings

Fuel density	943.9 kg/m^3
Fuel LCV	41680 kJ/kg
Trial Engine Load	35-50-75-90%

The trials were conducted as double runs and runs were planned in overlaying tracks and verified on the ship's ECDIS, see Fig.4.

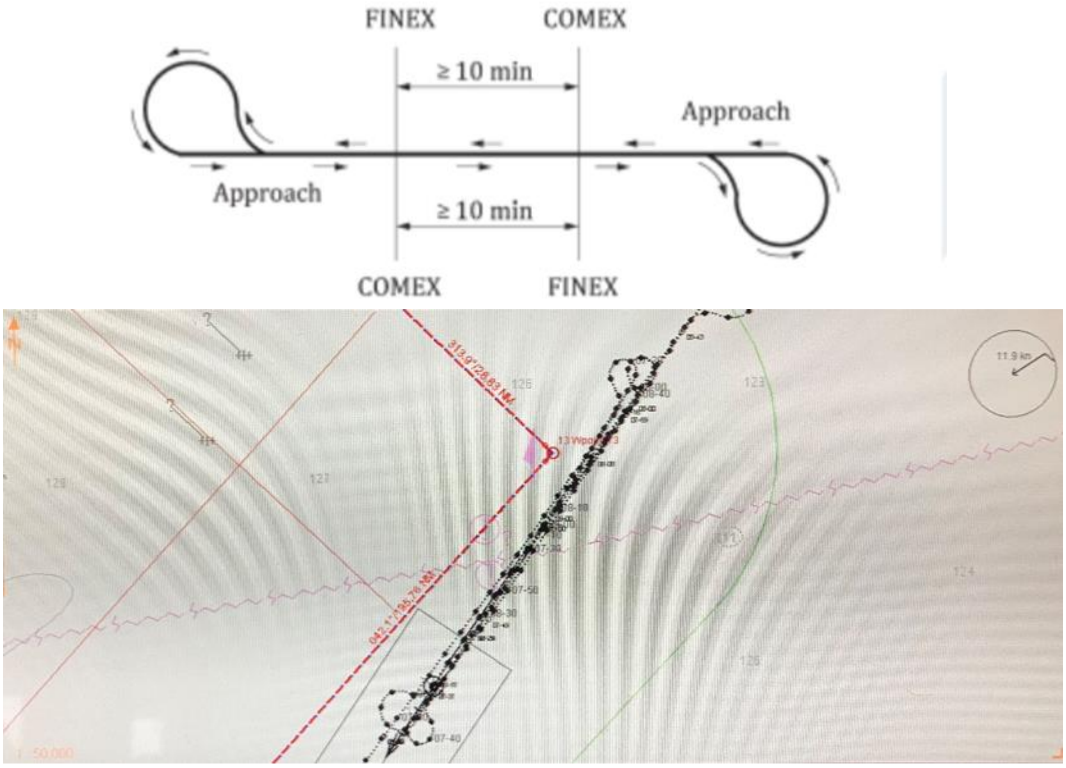

Fig.4: Double run scheme plotted on the ECDIS

5. The speed trial analysis

The collected data were all analyzed using the ISO 15016:2015 method. The correction methods used in the analysis were as in Table III.

Table III: Correction methods for environmental conditions

Parameter	Method
Waves	STA 1
Wind	Fujiwara
Current	Mean of Means method

All values were run through the analytics software and a set of resulting speed – power values for the reference condition (at ideal weather conditions) were then used in a comparison with the original values and an average difference was then used – for Case 1, as the calibration factor for the EEXI condition and for Case 2 as verification for the result and the method in use.

5.1. Case 1

In the comparison with the model test values for a sister ship, the average power reduction in the reference condition was found to be 8%. This reduction was then an indication of the improvement in performance by the implemented EETs in the last dry dock. The reduction was then used as a calibration factor on the model test values for the EEXI condition and a new EEXI value was calculated and issued in an EEXI Technical File which was approved by Class.

A comparison between values is found in Table IV.

Table IV:1 **Reductions in Power and Speed**

	Statistical Method	Model Test	Speed Trial
MCRlim / MCR	51%	57%	64%
Max speed after MCRlim - reduction	14%	11%	9%

For this vessel, there is a difference of 5% on the theoretical maximum speed from the statistical value to the actual performance of the vessel. For the MCRlim, the difference is 13%.

5.2. Case 2

The average power reduction in the reference condition was found to be 5%. This reduction was then an indication of the improvement in performance by the implemented EETs in the last dry dock. The result was accepted as the actual performance of the vessel and a second speed trial was held in the EEXI condition and a new EEXI was calculated and issued in an EEXI Technical File which was approved by Class.

A comparison between values is found in Table V.

Table V: Reductions in Power and Speed

	Statistical Method	Speed Trial Overridable EPL	Speed Trial Non-over-ridable EPL
MCRlim / MCR [%]	38%	44%	48%
Max speed after MCRlim - reduction [%]	28%	22%	20%

For this vessel, there is a difference of 6% on the theoretical maximum speed from the statistical value to the actual performance of the vessel. For the MCRlim, the difference is 6%. The reductions were quite large for this vessel and the option of introducing a permanent power reduction was considered. In the regulations, the Pme is 75% of the MCRlim instead of the the 83% for overrideable power limitations which will add to the available power for the vessel (shown last column in Table V).

5.3 The fuel oil consumption analysis

For the two cases, the fuel oil consumption was analyzed. The ME SFOC was calculated based on the measured power and the measured fuel oil consumption. The values were ISO corrected and compared to the ME FAT tests that were available for both case vessels. The measured values were compared to expected values (from the vessel model) and found in a valid range. A sample measured values are shown in Fig.5.

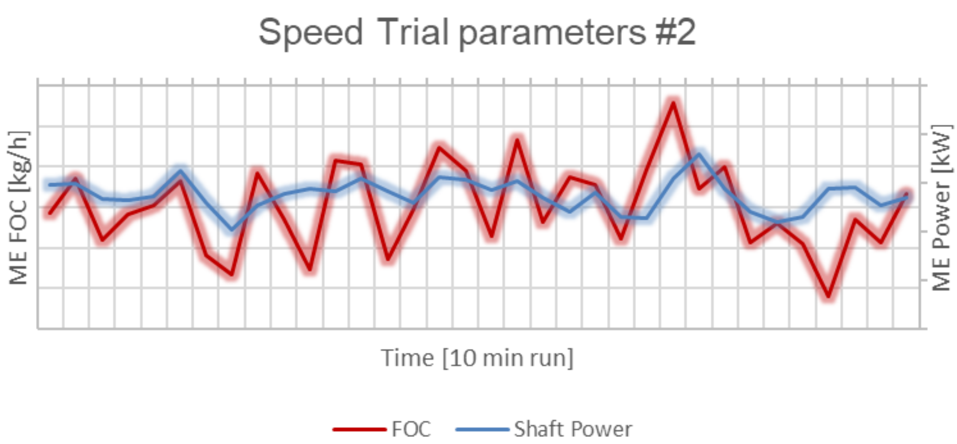

Fig.5: Sample Power and Fuel Oil Consumption values

Case 1: For this vessel, the speed trial was held in the reference condition and the results were as in Table IV.

Table VI: SFOC diff

	Speed Trial
SFOCiso delta	4%

The result is quite good compared to the age of the engine (2008) and the delta is quite consistent on all engine loads.

Case 2: For this vessel, the two speed trials were used to find the actual SFOC for the vessel. The result is as given in Table VII. The result is quite high even for an engine of this age (2008) and the delta is quite consistent on all engine loads.

Table VII: SFOC diff

	Speed Trial
SFOCiso difference	13%

The engine degradation over the years can vary depending on the engine maker and type, the maintenance schedules of the engine and for the actual performance status of the engine. There are rules of thumbs within the different shipping companies and often it is experienced based. In any case, the actual information can be used in setting the baseline for the vessel with respect to speed, power and consumption for a future performance monitoring perspective.

6. Conclusions

The introduction of the MEPC.1/Circ. 901 has made it possible to add flexible speed trials for the verification of the performance of vessels. The flexibility with regards to time, area and the verification of results gives the opportunity to fit the trials into a busy vessels schedule.

The inclusion of data from a high frequency performance monitoring system as data used for the performance analysis adds to the use of large data amounts and to increased digitalization at sea. The precision, the timeseries and the availability (connectivity) makes it possible to perform the speed trials when the conditions are met.

The digital model of the ship provides a theoretical overview of the vessel's performance i.e,. how the vessel would perform when it was new. It further adds to the verification of the measured data with a sanity check and if data are within the expected values. After the speed trials, the model can be updated with the actual performance values and used as a baseline model for the future performance evaluation of the vessel.

The results with respect to the EEXI verification show that the vessel now is assessed according to the actual performance of the vessel. The speed trials are performed to the approved standards and with recognized methods and not to unknown or random practices. The standardization further makes the verification process by Class smoother and the transparency of the analysis process is clear due to the availability of the time series from the performance system.

The results further have the desired effect on the EEXI, and the vessel has had a fair assessment of the performance due to the usage of the actual values. The statistical evaluation shows that the vessel is penalized with regards to power limitation and speed reduction. The advantage of using the speed trial results is obvious and for both case studies, the vessels flexibility in adapting to the market has been maintained to some extent.

As a remark to the reduction of power of the engines and the future operation on lower engine loads, it is assumed that the engines will run less efficiently since they will be operating on a less efficient area when looking at the SFOC curve. Typically, in cases of derating engines, which the EPL would be a case of, modifications to the engines with respect to shifting the SFOC curve to “the left” i.e., move the efficient area to lower loads, is often included in the derating. If this is not considered in the installation of the EPL, the engines could encounter maintenance issues over time and the ability of running the engine regularly on high loads is not possible without overriding the EPL.

The EEXI regulations are introduced as a short-term measure to reduce the CO2 emissions from shipping and reduction of power of the main engines does in theory also reduce the emissions. The question is whether it actually reduces emissions since the market over time has adapted to lower speeds already. And the overpowered badly designed older tonnage where the EEXI regulations should have an effect already are operating in this changed market. Since the EEXI is introduced along with the CII regulations, the combined effect probably will lead to replacement of older tonnage. Since the regulations are new and there are no agreed sanctions to vessels that do not comply with rules, it is still to be seen what the full effect on vessel operations will be.

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CII Performance Forecast for Bulk Fleet

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Abstract

This study investigates a method to forecast a vessel's end-of-the-year Carbon Intensity Indicator (CII) value based on the vessel's historical operational patterns and vessel-specific performance model. The forecasting model's accuracy and error margins are evaluated based on the amount of available data as well as the model's sensitivity to unexpected events is discussed. The study focuses on dry and wet bulk fleets.

1. Introduction

The shipping industry plays a crucial role in global trade, facilitating the movement of goods across the world's oceans. However, the environmental impact of maritime transport, particularly its contribution to greenhouse gas emissions, has raised significant concerns. The International Maritime Organization (IMO) has set a target to be net zero in carbon emissions by year 2050. This is a step up from the previous target to have at least 50% lower absolute emissions by that year, when compared to the emissions in year 2008. To address these concerns and move towards a more sustainable maritime sector, there has been a growing emphasis on developing new regulations to measure the industry's carbon emissions, from which the carbon intensity indicator (CII) is one example.

CII is an operational index, which measures all the carbon emissions from all ballast and laden voyages, anchorage, and port stays, divided in bulk ships by the deadweight and distance sailed in a year (grams of CO_2 per DWT mile) for ships with gross tonnage over 5000. A rating from A to E is assigned to each ship every year based on requirements that will become more stringent year by year. Besides the fact that ships with higher ratings will have a privileged market position by helping the shipping stakeholders and cargo owners to prioritize well-rated vessels, the vessels that achieve a D rating for three consecutive years or an E rating in a single year must develop a corrective action plan as part of the SEEMP.

This article focuses on exploring the use of vessel operational data and vessel-specific performance models to predict the CII for bulk carriers and tankers, two critical components of the global shipping fleet covering a total of 59% of the world tonnage. Understanding and forecasting the CII performance for these vessel types are vital steps toward improving their overall environmental impact and preventing any commercial consequences from a bad CII rating.

The accurate prediction of CII is a complex task due to the multifaceted nature of vessel operations and their dependency on numerous factors. The variations in operating conditions, routing, and weather conditions, hull fouling, among others, contribute to the challenges in establishing robust forecasting models. In addition, the model does not have transparency on any possibly planned dry docking or energy-saving equipment installations, that would significantly impact the carbon intensity of the vessel's operation for the remainder of the year.

The primary objective of this research is to evaluate the predictability of CII for bulk carriers and tankers using vessel-specific models and available vessel operational data. By leveraging vessel operational data and employing vessel-specific performance models, we aim to shed light on the most critical factors influencing CII and their potential impact on the overall environmental footprint of bulk fleets. Such insights will not only benefit ship operators and owners in optimizing their operations but will also assist policymakers in formulating effective regulations and incentivizing cleaner maritime practices.

It is also demonstrated how digital solutions, such as NAPA CII simulator, play an irreplaceable role to gather onboard operational data, track and understand performance in real time, and facilitate collaboration between stakeholders in planning next actions to meet requirements and improve their competitiveness.

In the following sections, we will delve into the methodology and analysis process employed as well as the key findings derived from our investigation. Additionally, we will discuss the limitations of our research and the criticism the CII has received from the industry. Some criticalities in terms of correlation between the current formulation of the CII and the benefits for the society have been highlighted in the literature and will be discussed in section 4. It is nevertheless relevant to assess the collocation of the global fleet in terms of CII ranking, and estimate to which extent it has the potentiality to influence the operational profile of the vessels and affect the maritime industry on market positioning, business models and communication strategy.

With the urgency of mitigating climate change and the rising demand for environmentally responsible shipping practices, the outcomes of this study are anticipated to contribute to the ongoing efforts of making maritime transport more sustainable, efficient, and environmentally friendly.

2. Carbon Intensity Indicator forecast

2.1. Methodology

A fundamental aspect, especially when ship operational performance is linked with regulatory framework as in the case of CII, is the ability to predict the score in the future and in particular at the end of the year, when the first CII evaluation will be carried out.

Data analysis plays here a key role. By analyzing the past operations, the model can learn the typical sailing speed of the vessel in different conditions, areas and weather encountered, the time spent in port for loading and discharging, the idle time, and the consumption in the different phases of the voyages. It also accounts for past maintenance and consumption trend, as shown in Fig.1, by applying a hull performance degradation correction.

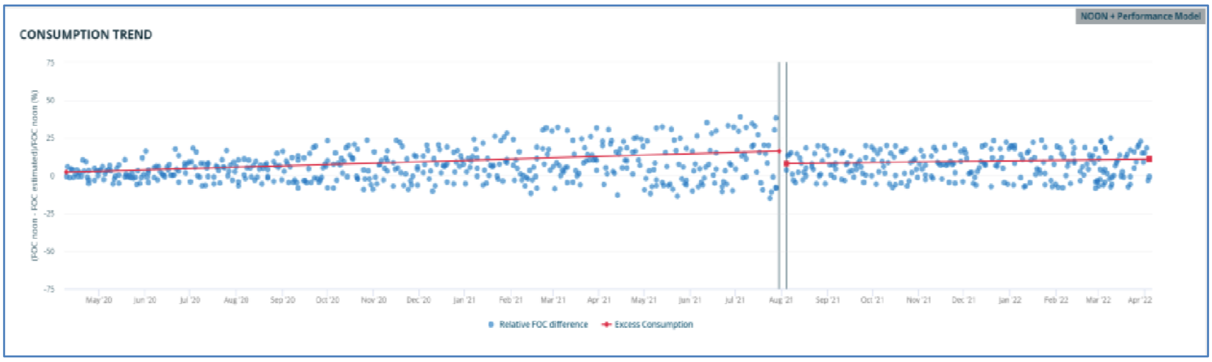

Fig.1: Effect of fouling and maintenance show in the consumption trend graph

Global AIS information processing crossed with ship specific operational reports and measurements are combined with environmental conditions and allow to understand the speed profile, operational drafts in laden and ballast, port calls, waiting time and maintenances, and to develop models for the prediction of vessels' specific performance, additional consumption from auxiliaries and boilers, and typical voyage process.

Different forecasting models for the end-of-year CII score have been studied, from the simplest assumption of unvaried operations with respect to the previous year, which serves as a baseline, to the most comprehensive approaches attempting to simulate in detail the future operations.

Not always the most complex model offers the best results. Instead, a balance must be found to maximize the statistical significance of the past information, the reliability of the simulated events and processes, and the representativity in catching alterations in the operational profile and technical performance. The selection of the model and tuning of the relative parameters have been finally driven by the minimization of the prediction error when applied to the historical data of several vessels with verified operational data reliability.

2.2. Accuracy evaluation

The accuracy of the method has been evaluated by comparing past predictions with the actual score achieved by the vessels. With the developed method which monitors the evolution of the vessel's operational profile in real time, in 90% of the cases the estimation error is below 15% already in March and to around 10% before the half of the year. For half of the vessels the result was closer than 5% of the predicted score regardless of the prediction date. Fig.2 summarizes the results of the accuracy evaluation.

As a comparison, by assuming the CII score in the current year to be the same as in the previous year, a significant error can be expected, with a 90% confidence interval between 20% and 25%.

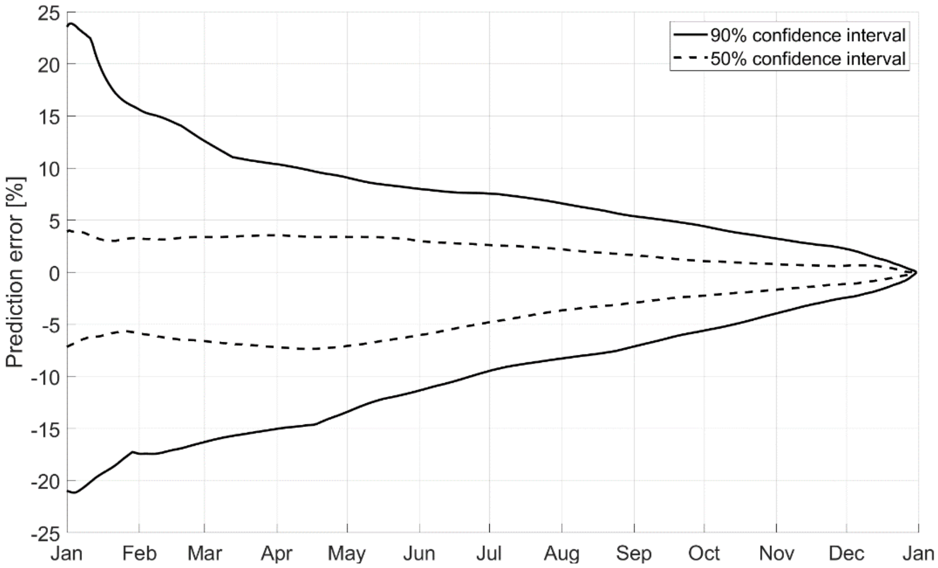

Fig.2: Confidence intervals of the predictions

The accuracy of the prediction model depicted in the previous figure refers to the basic case in which only past operations can be considered and no information is available on the future plans. One of the challenges in developing the methodology resided in the drastic modifications in the operational profile experienced by the shipping industry in the past year due to the pandemic and in part to the Ukrainian war. Consequently, the confidence levels might be conservative in a more stable period and will be recursively evaluated in the future.

However, the confidence intervals must be related to the changes in the operational profile of the vessels. For ships which operate in a regular way and do not incur in drastic technical modifications, the error will be close to zero. On the other hand, if in the upcoming months it is expected to install energy saving devices, drastically change the sailing speed to adapt to evolving market demand, or spend a prolonged time in port, the estimation accuracy can be affected. Modern digital tools allow to assimilate such information in the system to improve the predictions. Fig.3 shows an example of CII monitoring and prediction including the assimilation of information regarding maintenance and installation of energy saving devices planned for the future months. Furthermore, it is possible to insert future voyages and simulate their effect to facilitate the fleet operational planning and collaboration among different stakeholders, for instance in the stipulation of chartering contracts.

Fig.3: Example of CII prediction assimilating information about planned maintenance and installation of energy saving devices

2.3. Results

The prediction model discussed above has been then used to forecast the grades that vessels will receive at the end of the year, being first evaluation of the CII rating. The analysis focused on dry and wet cargo fleets as they cover more than half of the global merchant vessels. The results are summarized in Fig.4.

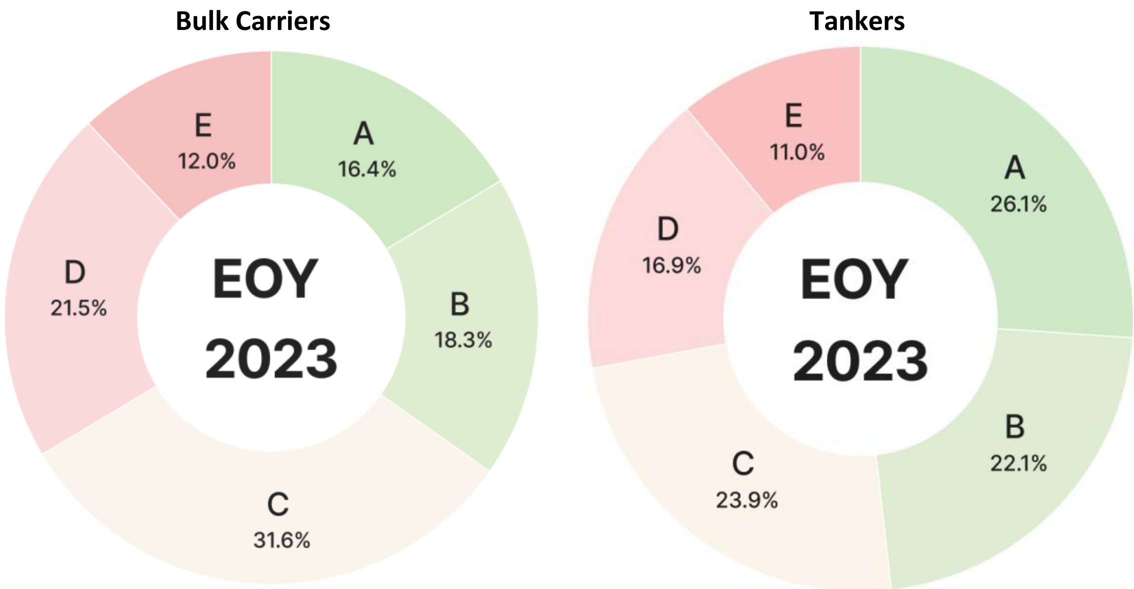

Fig.4: Predicted 2023 end-of-year CII distribution for dry bulk carriers

It has been found that one third of the bulk carriers will not achieve the minimum C-rating to be considered compliant with CII regulation, 12% of them will get a E-rating, as discussed in section 3, will already need to amend their SEEMP part III in 2024. About another third of vessels will achieve the required C-rating, but will still need to carefully plan the operations in 2024 considering that the thresholds will decrease by 2% every year until 2026.

The situation looks blighter for wet cargo shipping, with almost 50% of tankers expected to receive A- or B-rating. However, the portion of non-compliant vessels will be just slightly lower with respect to bulk carriers, with almost 28% of tankers falling in ranks D or E.

2. Consequences for the companies

The regulatory framework does not yet establish consequences or penalties for vessels not complying with the required CII ranking in 2023. Operators are however obliged to submit a SEEMP Part III Corrective Actions Plan before DCS Statement of Compliance can be issued for vessels getting a E-rating the previous year or a D-rating three years in a row.

An underlying assumption in the approach of the policy maker is that CII will foster a change in the industry driven by commercial reasons rather than regulatory enforcements. Nevertheless, more stringent requirements may result from the IMO revision of the regulation if the effects timeline will not align with the ambitious decarbonization schedule.

Besides the critical aspects that will be discussed in the next section, the CII has two undoubtable strengths with respect to the regulatory approaches proposed in the past:

- it requires a continuous change in the daily operations of the vessels instead of one-time evaluation of the technical performance, with year-to-year improvements
- it assigns an easy-to-understand traffic light mark which can be powerfully exploited in the communication in an era when the industry is under the microscope of a more and more environmentally conscious public opinion which stimulates responsible shipping initiatives such as Poseidon Principle and Sea Cargo Charter.

As a consequence, a comprehensive strategy to improve efficiency of the fleet will not only help complying with the regulation, but also enhance the attractiveness of the vessels and the competitiveness of the companies. On the contrary, a passive behavior can lead to a series of mid-term consequences which combined can jeopardize the business, such as:

- more difficult access to financial market
- lower negotiation power in closing chartering contracts
- lower freight rates
- increased insurance premiums
- higher port fees
- limitations or deprioritization in the access to ports

3. Criticalities of CII

The foundation of the CII approach stands on the fact that emissions are acceptable to the extent that they bring a benefit to society. Considering the CII equation in its summary form:

$$CII = \frac{\boldsymbol{Overall\ emissions} - Operations\ in\ ice - Cargo\ handling}{Reduction\ factors \cdot \boldsymbol{Capacity} \cdot \boldsymbol{Distance}}$$

and focusing on the main contributors highlighted, the concept is that the more goods are transported for a longer distance, with lower emissions, the better the CII rating.

Wang et al. (2021) listed a series of paradoxes demonstrating how any CII approach can cause a behavior not expected by policy maker leading to the opposite effect of increasing the overall carbon emissions. Differently, in this section we aim at focusing on the criticalities related with possible unfair consequences of the regulation rather than tricks to achieve the required CII rank.

1. The first critical aspects regard the fact that the capacity does not always relate the same way to the amount of cargo transported, thus to the benefit for the society. A voyage sailed in ballast condition will lead to fewer emissions and a better CII than the same voyage sailed in laden conditions. Ballast voyages are in some cases unavoidable, but a different approach could foster actions to limit them as much as possible.

2. Vessels regularly deployed in short voyages are disadvantaged with respects to long hauls. In fact, the time spent in waiting for berth availability, manoeuvring, loading, etc., is in proportion longer for the former. This may lead to prefer other means of transporting goods in shorter distances, for example by road, with a counter effect for the environment. Taking into account trades in a holistic way and the specificities of intermodal links would be important to achieve the goal of the regulation.
3. As previously discussed, the CII regulation can affect the attractiveness of vessels with lower ranks. As a consequence, the use of lower ranked vessels, which are discarded by the healthiest and the most environmentally conscious stakeholders, may be concentrated in specific trades or regions, increasing the disparity and the pollution in these areas.

4. Conclusions

After thrilling the shipping industry and dominating the news in the months crossing 2022 and 2023, CII lost a bit of momentum in the communication giving more space to the upcoming EU-ETS scheme. Nevertheless, ship owners must remain vigilant and keep updating and actuating the strategy to minimize the potential negative impacts of this regulation and instead get the most benefits out of it.

The paradoxes discussed in the literature, e.g. *Wang et al. (2021)*, are often deriving from attempts to put a patch on an uncontrolled situation. Although it is important to highlight these aspects, it is equally important to understand that such methods to achieve the required CII rating typically come with a reduction of the overall efficiency of the vessel and a lost in competitiveness with respect to competitors which apply a holistic and preventive strategy to comply with the regulation through an effective improvement of the performance of their fleets.

Decarbonization of shipping industry book represents a significant challenge and requires an effort from all players, *NN (2023)*. However, it does not necessarily need to undermine the business, on the contrary as all challenges it can also be an opportunity if a proactive approach is pursued. Companies which start investing now on the right solutions will quickly find themselves to be compliant, sustainable, and efficient, and ultimately have a competitive advantage.

The technology to prepare your fleet for tomorrow is already available. Digital tools such as NAPA Fleet Intelligence and Voyage Optimization can support in this endeavor to maintain the fleets in the preference of the charterers, cargo owners any stakeholder.

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Quantifying the Uncertainty of High-Fidelity Speed/Power Trials

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Abstract

Within the JoRes Joint Research project, the uncertainty levels for a speed/power trial was investigated. The sea trials were performed as accurately as possible, following the ISO15016:2015, best practices and incorporating calibrated wave buoys for measuring sea state and independent judgment of vessel draughts. Based on the analysis conducted, it can be concluded that for the presented case, consisting of a 50k DWT tanker trialled in moderate weather conditions, the overall uncertainty in shaft power—taking into account various sources of uncertainty such as shaft power measurements, wave correction, wind correction, and others — amounts to approximately 4 - 6%. This indicates that even with the implementation of rigorous and accurate sea trials, there will still be inherent uncertainties that can affect the estimation of performance gains.

1. Introduction

Reliable speed and power data play a vital role in assessing the performance and efficiency of vessels, optimising fuel consumption, evaluating propulsion systems, and ensuring economical operation. Therefore, it is crucial to conduct speed and power trials using standardised methodologies and equipment to obtain precise and trustworthy results.

In the pursuit of standardised and internationally recognised procedures for speed and power trials, significant efforts have been made by esteemed organizations, such as the Ship Trials and Analysis Joint Industry Project (STA-JIP) run by MARIN. The results of STA-JIP were adopted by the International Towing Tank Conference (ITTC), the International Maritime Organisation (IMO) and the International Organisation for Standardization (ISO). These entities have developed guidelines and standards, including the ISO15016:2015, which provide detailed protocols for conducting and analysing speed and power trials, encompassing methodologies, instrumentation requirements, and data analysis techniques. The utilisation of these established frameworks should ensure consistency, comparability, and credibility of trial results across different vessels and trial specialists.

For reliable and meaningful speed and power results, it is essential to adhere as strictly as possible to the ISO standard and execute the trials meticulously. This entails employing the appropriate instrumentation, calibrated equipment, and experienced specialists well-versed in conducting speed and power trials. Furthermore, adherence to the standard promotes procedural consistency, minimising potential errors and uncertainties that could compromise the reliability of the trial's outcomes.

Insel (2008) conducted an uncertainty analysis using Monte Carlo simulations, considering a set of sea trials with 12 sister ships. The analysis took into account a range of parameters such as displacement, water depth, water temperature, wind speed, and wave height. The study concluded that the bias limit, precision limit, and total error ranged between 3-5%, 7-9%, and 8-10%, respectively. Similar conclusions were reached by *Werner and Gustafsson (2020).*

In the case of the JoRes Tanker this research paper focuses on, the trials were carried out under favourable conditions. Expert specialists with extensive experience in speed and power trials led the efforts, employing state-of-the-art equipment (including a wave buoy) to gather precise data. The trials were conducted in weather conditions featuring wind speeds ranging from 6 to 11 kn and a significant wave height between 0.6 and 1.2 m. While not ideal, these conditions adequately represent practical scenarios where reliable results from speed and power trials are still sought after. The subsequent chapter will delve into the specific uncertainty components, their magnitudes, and their propagation into the final results, focusing on this particular case study.

2. Uncertainty components & their propagation

Uncertainty in the results of speed/power trials can be considered as originating from two distinct sources: the uncertainty associated with the measurements and the uncertainty arising from the analysis process, i.e. the different corrections made to arrive at results for the ideal condition (no wind and waves, deep unrestricted water of standard temperature and density, no current, correct displacement).

The different components have an effect on either speed or power. Below, the contributing components are discussed: the nature of their contribution, the magnitude of the standard uncertainty $u_c(y)$ for each component y, as well as how they propagate into the end result. The expanded uncertainty U is calculated as $U = ku_c(y)$, with k the coverage factor, taken as 2 assuming normal distribution, to arrive at a 95% confidence interval.

2.1. Uncertainties propagating to speed

The ship's speed through water is determined by measuring speed over ground by a GNSS system, and employing a current correction using the double runs in opposite directions.

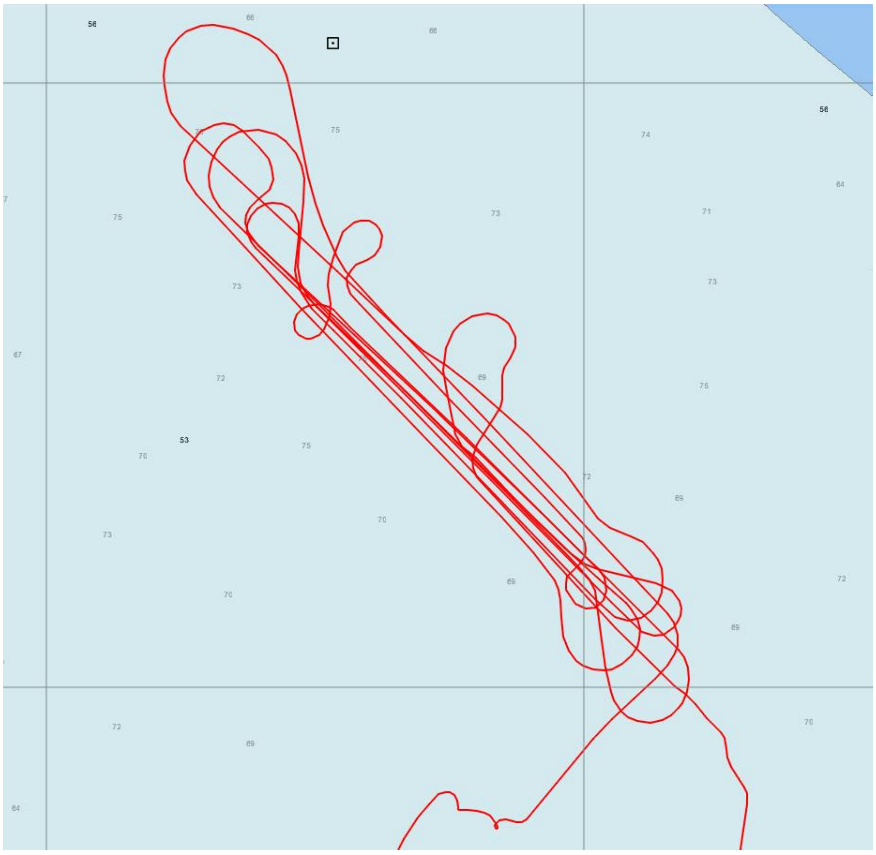


Fig.1: 12 double runs of the sea trials

- Measurement: GNSS uncertainty - The GNSS system used (CSI Wireless Vector PRO) has a documented standard uncertainty u(GNSS) = 0.5 m for horizontal position in DGPS mode. As prescribed in the ISO15016:2015 standard, speed over ground is determined from the distance between start and end positions of the run, divided by time. If both the start and end positions have a standard uncertainty of 0.5 m, the standard uncertainty on the distance d is $u_c(d) = \sqrt{(0.5^2 + 0.5^2)}$ = 0.7 m. Dividing that to the distance yields the uncertainty for speed over ground. The resulting expanded uncertainty $U(V_G)$ is around 0.005 kn for all run sets.

- Speed through water determination: current correction - The speed through water is calculated from for a run set (consisting of one or two double runs) by a current correction. ISO15016:2015 offers the choice of using either of two methods: the mean of means method and the iterative method. There is no general statement on the accuracy of these methods, making the evaluation for our purposes difficult. As a measure of uncertainty, the spread between the available methods and a hindcast current model (with its own, unknown uncertainty) is taken as a (be it crude) measure of the overall uncertainty on speed through water. The difference between both methods to the hindcast model is between 0.05 and 0.19 kn, depending the run set. These are taken as the expanded uncertainty of speed through water for the respective run sets.

2.2. Uncertainties propagating to power

The contribution of the uncertainties within the measurement chain of shaft power and the different correction methods used is detailed below.

2.2.1. Measured shaft power

The shaft power is determined from measured shaft torque Q_{ms} and shaft speed n_{ms} by $P_{ms} = Q_{ms} n_{ms} \frac{2\pi}{60}$.

The shaft speed is measured by an optical pickup aimed at a reflective tape on the shaft, passing once per revolution. If the pickup misses up to one cycle per run, the associated uncertainty in shaft speed can amount to U_n = 0.01 to 0.06 rpm (or: between 0.02% to 0.1% for the different runs (differences due to different shaft speeds and run lengths).

The shaft torque Q_{ms} is determined by measurement of shaft strain by a strain gauge glued to the shaft, Fig.2. As means to check installation uncertainty, two strain gauges were installed on the same shaft. From the strain ϵ_{ms}, shaft torque is calculated by $Q_{ms} = \epsilon_{ms} \frac{2}{k} G Z_P$. Table lists all the associated uncertainty components.

Fig.2: On of the two strain gauges installed on the shaft

- For ϵ_{ms} itself we consider three sources of uncertainty: the strain gauge's k-factor, the installation and the zero calibration.
  - The strain gauge's k-factor is listed by the manufacturer as expanded uncertainty $U = 1\%$.
  - The installation uncertainty was researched in the GRIP project, *Janse and Hasselaar (2014)* to be 0.55%. For this case, the mean difference between the two strain gauges on the same shaft is found to be 0.7%, which is used going forward.
  - The zero calibration was done both before and after the trials, with a difference of 0.3%.
- The shaft diameter was determined by measuring circumference of shaft, which is estimated to be within 1 mm accurate. The diameter is therefore within 0.3 mm accurate. It propagates into the shaft torque via the polar section modulus.
- The actual G-modulus for a specific shaft is not often tested, so the standard value of 82,400 N/mm^2 is taken. This value was chosen as a mean value during the STA-JIP. From that work, the spread was judged to be 2.5%, which is taken as expanded uncertainty propagating linearly into the shaft torque.

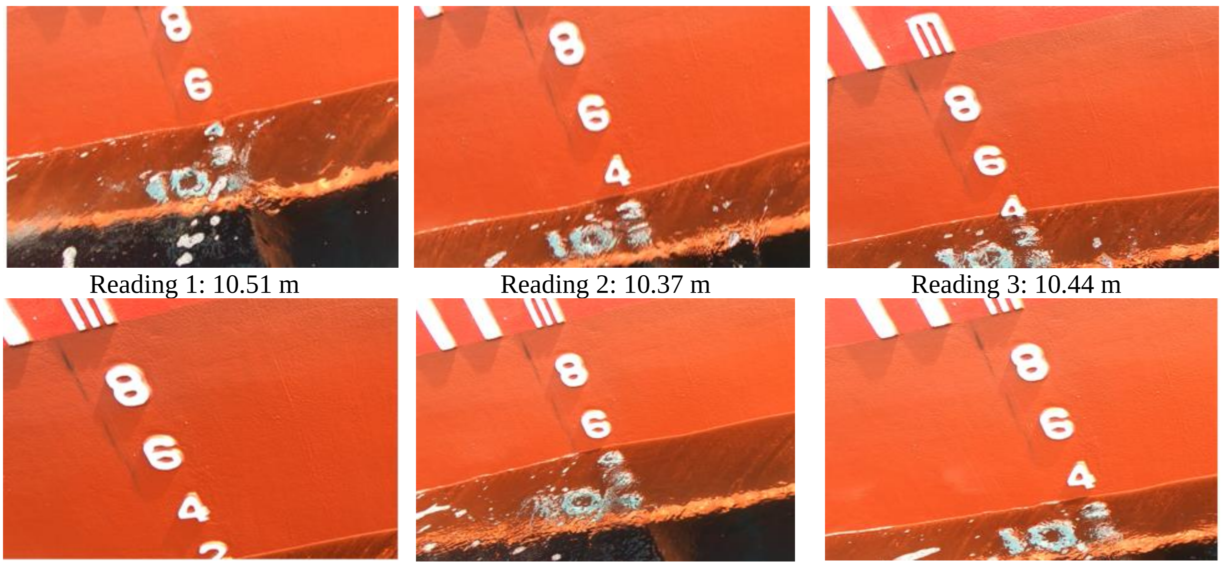
This results in a uncertainty on the measured shaft power of 2.8%, Table I. The dominant uncertainty in the shaft torque is the uncertainty associated with using the standard G-modulus. The uncertainty in shaft power is 2.8%, with the uncertainty in shaft speed having a negligible effect.

Table I: Uncertainty components in Q_{ms}

Component	U	Propagation to Q_{ms}	Propagated
k-factor	1.0%	Linear	1.0%
Installation error	0.7%	Linear	0.7%
Zero calibration	0.3%	Linear	0.3%
Shaft diameter	0.1%	Via polar section modulus: $Z_P = \frac{\pi}{16} D^3 \sim D^3$	0.2%
G-Modulus	2.5%	Linear	2.5%
Total			**2.8%**

2.2.2. Displacement: draught reading, effect on displacement

The ship's displacement is determined by reading the draught marks, Fig.3. For this case, the uncertainty on the draught readings, performed at sea, was determined to be 27 mm, *Ponkratov and Struijk (2022)*, taking into account differences between observers, methods of observation, draught change over the trial duration and the slight rolling motion of the vessel during observations.



Reading 1: 10.51 m | Reading 2: 10.37 m | Reading 3: 10.44 m

Reading 4: 10.20 m | Reading 5: 10.56 m | Reading 6: 10.37 m

Fig.3: Sample draught measurements after the trials (consequent waves crests and troughs at transom)

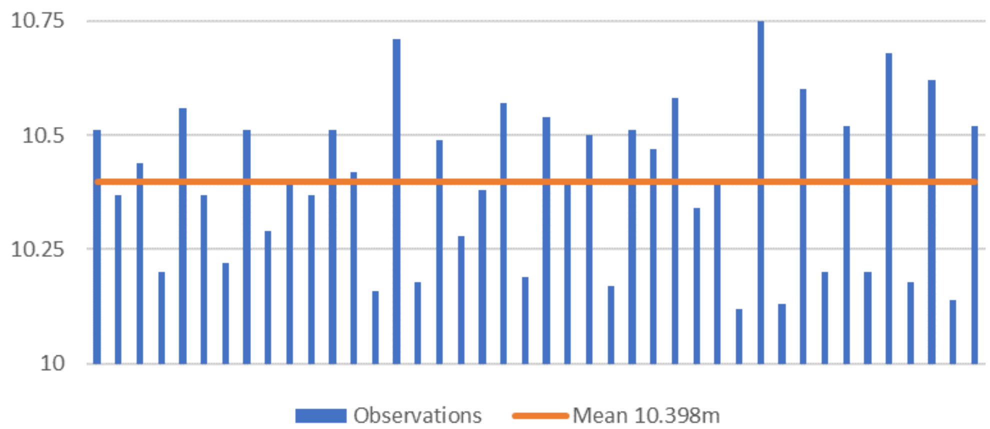


Fig.4: Deriving the mean draught at the transom by averaging consequent waves crests and troughs

From the hydrostatic tables it was calculated that the impact of such deviation would be 0.3% on the displacement volume. This propagates via the admiralty coefficient, resulting in 0.2% propagated uncertainty on power.

2.2.3. Wind correction

The added resistance due to wind is determined by $R_{AA} = \frac{1}{2}\rho_A C_{AA}(\Psi_W) A_{XV} V_W^2$. Within the wind correction, the following components are identified:

- The used wind resistance coefficient C_{AA} from the ISO standard is one for a general tanker vessel, not the specific vessel. Review of literature and MARIN's internal database shows a spread in C_{AA} values of around 0.1 for different tankers. This is about 16% of the used C_{AA} values, and is taken as the expanded uncertainty propagating linearly into the wind correction.
- The measurement uncertainty within V_W is stated by the manufacturer of the used anemometer (Gill WindSonic) as 2%. This is taken as the expanded uncertainty propagating quadratically into the wind correction.
- The frontal wind area A_{XV} is determined from drawings at an estimated accuracy of 3%, taken as the expanded uncertainty propagating linearly into the wind correction.
- Placement of the anemometer - in practical use of an anemometer in a ship's mast, it is unavoidable to be in a region of disturbed flow. Taking from the research by *Moat (2003)*, for the setup in this case the disturbance on wind speed is estimated to be in the order of 5%, propagating quadratically into the wind correction.
- Similarly, *Moat (2003)* states the wind angle can be disturbed by about 10 degrees, leading to a different C_{AA} value being used for that different angle of about 11%, propagating linearly into the wind correction.

With the above, the total uncertainty on the wind correction is 22.5%. The propagation is proportional to the magnitude of the wind correction, which in the presented case is between 2% to 6% of measured power, leading to propagated expanded uncertainty levels between 0.5% to 1.4% of measured power (both due to changing weather and the differences in magnitude of measured power over the runs).

2.2.4. Wave correction

The STAWAVE-2 method is used to correct for the added resistance due to waves. Within the wave correction, we can identify the following contributions:

- Measured wave height - the uncertainty of measured wave height by the used wave buoy (Datawell DWR), Fig.5, was determined by *Van Essen (2018)* to be 2%. This propagates quadratically into the wave correction to an expanded uncertainty level of 4%.
- Wave added resistance method - the documented uncertainty of the used method (STA-WAVE-2) is 31%.

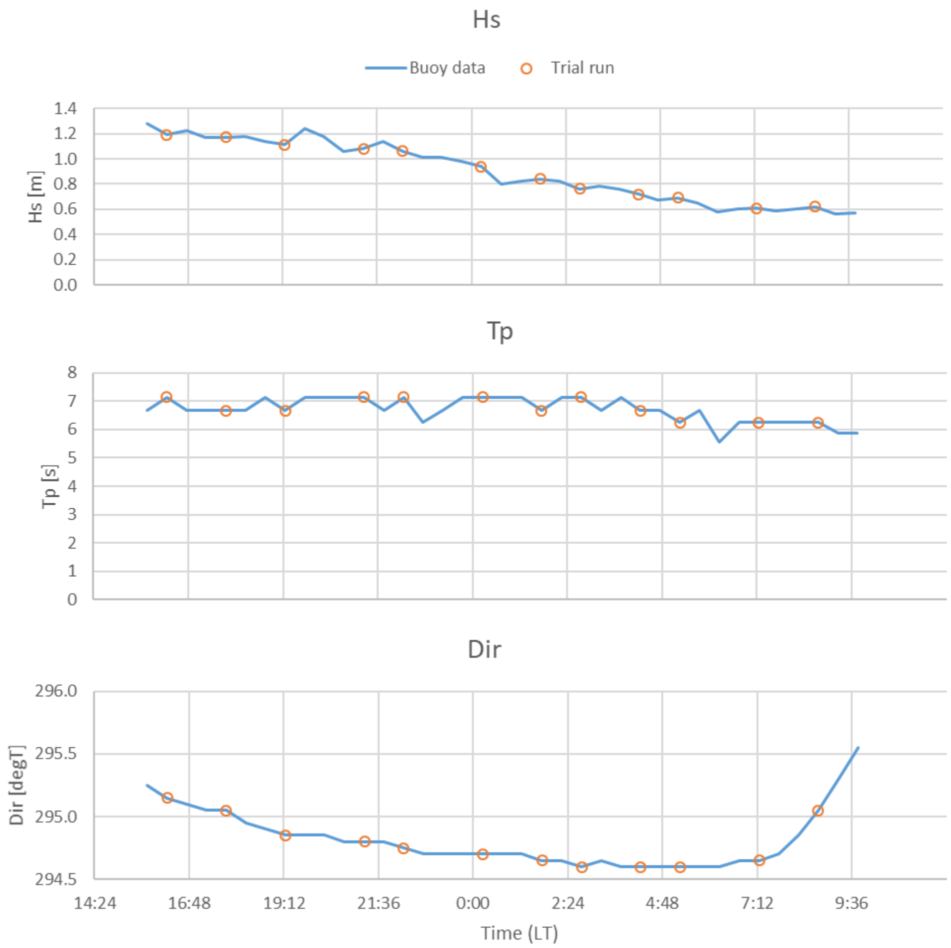


Fig.5: Wave buoy data (wave hight, period, direction)

The total uncertainty of the wave correction is 31.3%. Analogous to the wind correction, the propagation is proportional to the magnitude of the correction made, which in the presented case is between 1% to 9% of measured power, leading to propagated uncertainty levels between 0.3% to 2.8% of measured power (both due to changing weather and the differences in magnitude of measured power over the runs).

2.3 Total uncertainty on speed and power

Table II gives a summary of all the uncertainty components discussed above, and their propagation to speed and power. Alternatively, if one is to draw a bandwidth around the obtained speed/power relation obtained from the corrected trial points and their respective error bars in speed and power for all run sets, the shaded area in Fig.6 offers a visual representation. The shaded area encompasses a bandwidth in power varying from 4% at the higher speeds to 6% at the lower speeds.

Table II: Summary of the total propagated uncertainties

	Propagated uncertainty per run set			
Run set	1	2	3	4
GNSS	0.1%	0.0%	0.0%	0.0%
STW	2.1%	0.7%	0.4%	1.0%
Total propagated to speed	**2.1%**	**0.7%**	**0.4%**	**1.0%**
Shaft power measurement	2.8%	2.8%	2.8%	2.8%
Displacement	0.2%	0.2%	0.2%	0.2%
Wind correction	1.4%	1.1%	1.2%	0.5%
Wave correction	2.8%	1.6%	0.7%	0.3%
Total propagated to power	**4.2%**	**3.4%**	**3.1%**	**2.9%**

3. Conclusion

Based on the analysis conducted, it can be concluded that for the presented case, the overall uncertainty in shaft power—taking into account various sources of uncertainty such as shaft power measurements, wave correction, wind correction, and others—amounts to approximately 4 - 6%. This indicates that even with the implementation of rigorous and accurate sea trials, there will still be inherent uncertainties that can affect the estimation of performance gains.

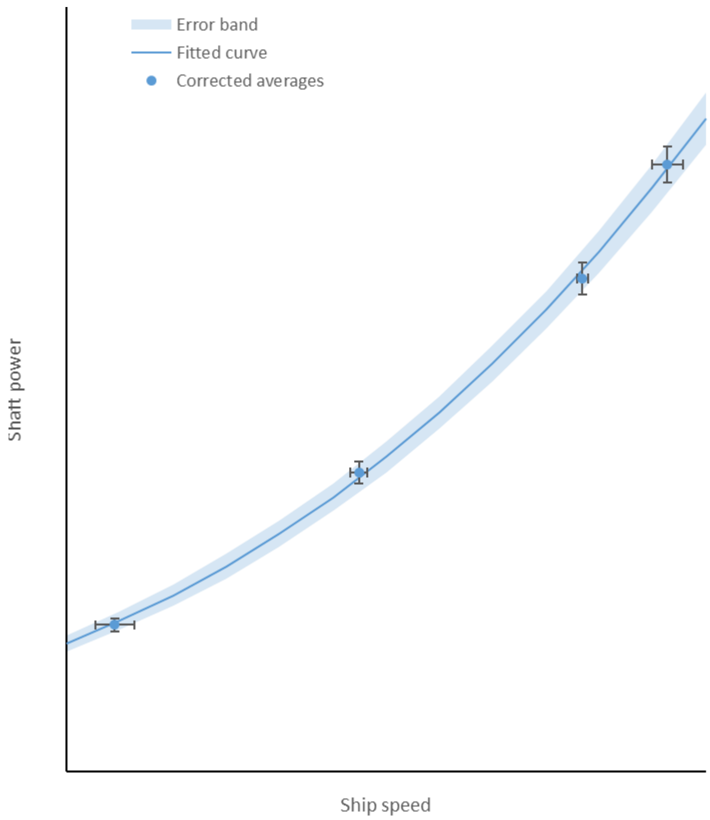


Fig.6: Corrected trial results with error bars per run set and shaded bandwidth around obtained speed/power relation

Therefore, if a shipowner intends to assess the impact of an energy-saving device installation or any other modification on the vessel's performance, it is important to consider the magnitude of the expected gain. If the anticipated gain falls within the stated uncertainty band, it may not be reliably captured or distinguished from the inherent uncertainties associated with the measurement and correction processes.

It is crucial for shipowners and stakeholders to be aware of the inherent uncertainties in power determination and to interpret the results of sea trials accordingly. If low uncertainty levels are warranted to e.g. prove a performance gain, it is of vital importance to undertake the sea trials in very favourable weather conditions, such that the propagation of the correction method's uncertainties to the end result is limited.

Additionally, ongoing efforts to improve measurement techniques, reduce uncertainties, and enhance the accuracy of power calculations can further refine the assessment of performance gains and help minimize the impact of uncertainties on decision-making processes.

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Alternative Approaches for Collecting High Frequency Performance and Consumption Data

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Abstract

Recent studies and new products on the market show a clear benefit of using high-frequency ship performance and consumption data over manual noon reports for optimization of shipping operations. Unfortunately, the majority of ships are not equipped with auto-logging sensors, such as mass flowmeters and shaft power meters, and existing retrofit solutions on the market are too costly. Moreover, those solutions are not suitable for operators of time-chartered vessels. This paper describes novel non-invasive solutions for automated high-frequency ship performance and consumption data collection, alternative to existing retrofit approaches. It covers approaches suitable for both mechanically controlled and electronically controlled engines. The results are compared to the "golden standard" of data collection set by ISO 19030.

1. Introduction

The idea of data driven ship performance optimization has been gradually accepted by the shipping industry over the last 30 years thanks to the development of accessible ship to shore connectivity solutions. Consumption, performance, and weather data reported by the crew through the means of noon reports started to be used for modelling of the hull condition, prediction of performance, vessel routing and other tasks of shipping operations optimization by ship owners, charterers, and technical management companies. However, the nature of this manually collected and reported information impacted the quality of the data. Very often noon reports require some sort of verification and cleaning, that is often done automatically or even manually by a shore team. Averaging of the reported parameters from noon to noon is also impacting the usability of the produced data.

Introduction of machine learning proposed new solutions to many existing optimizations tasks as shown by *Petersen et al. (2020)*. Nonetheless, those solutions rely more than ever on the quality and the quantity of the datasets they are trained on. While several attempts are being made to train those algorithms on noon reports collected from hundreds of vessels, many studies show that only auto-logged high-frequency high-quality data can produce reliable models. Transition from noon reports to automated high-frequency reporting was started by many shipowners and was assisted by different vendors. Most of the navigational data, such as GPS location, ground speed and log speed, together with weather data can be rather easily extracted from the bridge equipment and delivered to the shore almost in real time. Alternative solutions relying on publicly available AIS and metocean data can also be used for certain use cases.

Unfortunately, data related to propulsion and consumption is a lot more difficult to collect. Auto-logging sensors, such as mass flowmeters and, especially, shaft power meters are still rarely found on merchant vessels (except, probably, containerships). Retrofits are too costly for many shipowners, and we still see many newbuilds coming out with volumetric flowmeters and analogue AMS.

One of the reasons cited by the shipowners for not equipping their vessels with auto-logged sensors is that the benefits of such devices are ripped by charterers while the cost is on owners. On the other side the majority of charters do not have a possibility to access the ship's machinery and install required sensors even on time-chartered vessels.

Also, many OEMs (original equipment manufacturers) are locking down access to the digital interfaces of their modern equipment (electronically controlled main engines, generators, AMS, etc.). Certain vendors provide access to high-frequency machinery data through maintenance contracts but claim the ownership of the data to themselves, and not many shipowners have enough negotiation power to adjust those contracts. As a result, the only data about the machinery performance and condition we can work with is limited to a couple of day-averaged parameters such RPM, running hours and temperatures in the noon reports.

In the following chapters we will discuss what data must be collected for evaluation of vessel's performance and consumption and what methods can be used to collect this data without installation of auto-logging sensors, suitable for owned and time-chartered vessels. We will also compare the quality of collected data using those methods to the "golden standards" of the industry.

2. Vessel consumption and performance measurement

Fuel is the major cost factor for almost all means of transportation and precise fuel consumption measurement is a prerequisite for any type of performance optimization. Several methods can be used to measure vessel's <u>fuel oil consumption</u> and we will discuss them in the next section.

Another prerequisite for vessel performance optimization is the ability to measure the performance and, more importantly, to detect the changes in this performance. To unify different approaches, the industry has developed the ISO 19030 standard, *ISO (2016),* that is widely used as a reference for building modeling and optimization solutions. The standard was developed to be used with high-frequency data collected from onboard sensors. It defines a "default" method in its part 2 for measurement as well as "alternatives to default method" in its part 3, when certain elements (sensors) of the method are not available on a particular ship. The default method defines the following set of "primary parameters" for measuring changes in hull and propeller performance:

- speed through water (STW)
- delivered power (propeller power)

And secondary parameters:

- wind speed and direction
- speed over ground (SOG)
- ship heading
- shaft revolutions
- static draft
- water depth
- rudder angle
- seawater temperature
- ambient air temperature
- air pressure

The above parameters can be split into 3 groups:

- <u>power</u> parameters (delivered power and shaft revolutions)
- <u>navigation</u> parameters (STW, SOG, heading, rudder angle, draft)
- <u>environment</u> parameters (wind, sea, air)

We will leave navigation and environment parameters outside of the scope of this study and cover fuel oil consumption and power measurement.

2.1. Fuel oil consumption measurement

While the departure/arrival tank sounding is still considered by certain ship owners as "the most reliable way" to calculate the total fuel oil consumption, this method is not suitable for performance analysis methods that require consumption data during the voyage.

The industry currently employs four techniques for fuel consumption monitoring during the sea passage:

- Tank sounding (manual or automated) - Tank sounding during the voyage is more suitable for ROB (remaining on board) reporting rather than the momentary consumption due to the nature of indirect measurement of the fuel flow and due to a number of non-measured external parameters that affect the calculations (weather and sea state, temperatures, etc.).
- Estimation from engine parameters - Estimation of consumption from different engine parameters such as RPM/running hours/injection counters/etc. is mostly used on smaller vessels (e.g. tugboats, coastal traders) that are not equipped with any type of fuel flow meter. The margin of error of such indirect estimation is usually high because it depends on the condition of the engine and some parameters (e.g. power) that are not measured directly.
- Volumetric flow - Volumetric flow meters are the most common flowmeters found on merchant ships and can provide accuracy between 0.5% and 2% if maintained properly, https://www.insatechmarine.com/products/fuel-performance/performance/insatech-fuel-consumption-system. However, they can only report the volume flow (in liters) that is not enough for consumption monitoring, because the consumption is measured in mass flow (MT) and a conversion must be done that requires fuel oil temperature and specific gravity of the fuel in use. Certain volumetric fuel flowmeters available on the market are equipped with a temperature probe and even have an option to enter specific gravity in order to automatically calculate mass flow.
- Mass flow - Coriolis type mass flowmeters can directly measure the mass of consumed fuel and are considered as the "golden standard" of fuel consumption monitoring with an accuracy of 0.1%, *O'Banion (2013)*. Such high accuracy, however, comes with high price that slows downs the adoption of mass flowmeters by ship owners. Certain customers also complain about the complexity of the installation of Coriolis mass flowmeters and their sensitivity to vibration of high-speed engines.

A special procedure is applied for fuel consumption monitoring on vessels with a common (or mono) fuel system (shared between main engine and auxiliary engines, Fig.1), no matter if volumetric or mass flowmeters are used. Such systems usually require at least 3 mass or volumetric flowmeters (ME in, AUX in and AUX out). With the 3-meter system, the total fuel consumption is monitored by flow from fuel tank to settling tank. A set of flow meters, installed on the common auxiliary fuel supply line and return line, provide the total consumption measurement of the auxiliary engines and the main engine fuel consumption can be calculated by subtraction. The readings of all flow meters (and corresponding FO thermometers if required) must be done simultaneously, that increases the chance of human error.

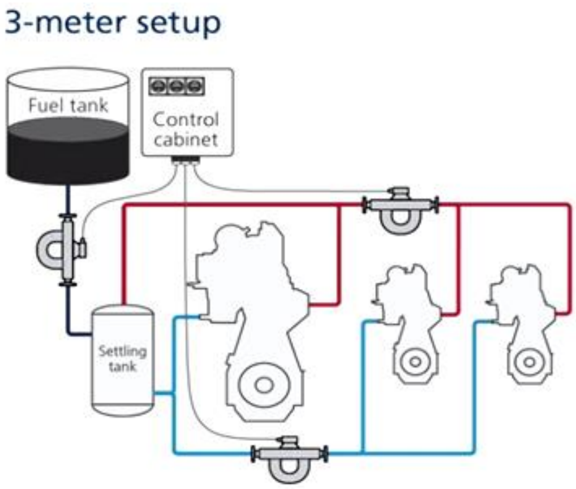


Fig.1: Common (or mono) fuel system. Marine Fuel Flow Meter, Consumption Systems & Measurements, Insatech Fuel Consumption System

2.2. Delivered power measurement

ISO 19030:2 stipulates that delivered power shall be calculated in one of the following ways:

- approximated from shaft power measured by a torsion meter
- or based on calculations of brake power from an engine specific SFOC reference curve

The most reliable method and the "golden standard" for power data collection is a torsion (torque) meter. There are several types of torque meters on the market based on strain gauges, acoustic strings, lasers, and other technologies. Unfortunately, this type of device is still rarely found on merchant vessels, except for container ships. The reason is the high cost of this sensor and complexity in installation and maintenance.

Reliance on SFOC reference curve brings a certain level of uncertainty. It is highly dependent on the accuracy of fuel oil mass flow measurement but is also influenced by changes in SFOC over time due to engine degradation.

Although not mentioned in ISO 19030:3, for two-stroke engines directly coupled to propeller (no gearbox) without shaft generator it should be possible to estimate delivered power from the engine power. Due to the friction in thrust bearings the delivered (propeller) power will be lower than the engine power, but the later one can be monitored without any additional equipment as following:

- for electronically controlled engines the engine power can be monitored via a PMI (Performance Measurement Indicator) or similar system
- for mechanically controlled engines the engine power can be estimated from fuel index using power estimation curves

3. High-frequency data availability

ISO 19030 was developed to be used with high-frequency data. And for hull and propeller performance assessment recommends 15 s (0.07 Hz) sampling rate (split and filtered in 10 minutes blocks). Such frequency of measurements can only be achieved with auto logging sensors. Most high-performance sensors such as mass flowmeters and torque meters are digital by design and are equipped with a digital interface (e.g. Modbus) that makes automated high-frequency data collection straightforward.

Unfortunately, the level of digitalization of merchant fleet is very low. *Guldteig (2022)* discovered that only 15% of vessels have electronically controlled engines. Digital by design sensors, such as mass flowmeters and, especially, shaft power meters are still rarely found on merchant vessels (with containerships being a notable exception). It is also surprising to see many newbuilds coming out of shipyards with analog equipment, such volumetric flowmeters and analog AMS (alarm and monitoring system) and no torque meter installed.

Another reason for slow adoption of high-performance auto logging sensors is that very often the main beneficiary of such devices is not the shipowner who installs them but a charterer who uses those sensors for performance optimization and costs reduction. And the majority of charterers do not have the possibility to access the ship's equipment and install required sensors even on long time-chartered vessels.

All the reasons listed above have led to the situation when high-frequency vessel consumption and performance data is not available and noon reports remain the only source of data accessible to fleet performance managers. This manually collected data is very difficult to work with because it is averaged over one day plus often contains human errors.

Fortunately, thanks to recent technological advancements, we are now able to present alternative approaches for collecting high-frequency performance and consumption data from existing equipment, suitable for owned and time-chartered vessels.

3.1. Collecting data from analog equipment

Unless we are talking about unmanned vessels, all existing ships and their equipment are designed to be monitored by humans and humans do not connect their brain to machines using some sort of wires. From the inception, the human-machine interface was mostly visual and based on instruments (also known as gauges) placed directly on the equipment or grouped in dashboards. And nowadays the crew is collecting the information from onboard machinery in the same way – by looking at those instruments, probably writing the values down on a piece of paper or typing them in some sort of software before sending it to shore. However, the crew members can only perform this task a limited number of times per day (or even per week) because of other tasks they are assigned to and, sometimes, because of the difficulty to access some of those gauges (e.g. FO flowmeters and thermometers in the engine room).

With the advancement of AI and computer vision algorithms it became possible to make computers perform the same task but an any required frequency. EYEGAUGE has developed and patented a technology that can “read” the gauges and transform those reading into data that can be delivered to the shore in near real time. This technology can be dubbed as an “OCR for the equipment”. The setup consists of a set of IP cameras installed in the locations around the ship where analog machinery dashboards and individual gauges are already present: in the engine control room, in the engine room, in the cargo control room, or on the bridge. The transformation of the images taken by cameras is done onboard (as it is said “on the edge”) into telemetry by a processing server running AI and computer vision algorithms Fig.2.

Fig.2: Data collection from analog equipment using AI powered cameras

3.2. Collecting data from digital equipment

Of course, we see more and more digital equipment onboard ships. Paper maps have disappeared and all navigational equipment on the bridge is integrated, thanks to the public standards such as NMEA0183, and the corresponding data is easily accessible.

Moreover, recently built ships are usually equipped with electronically controlled engines, modern alarm and monitoring systems that are digital by design, Fig.3. The most logical way to collect data from such equipment is through digital interfaces and protocols (Fieldbus, MODBUS, CANBus, OPC-UA, MQTT, etc.) that we find in ground or air transportation and other industries. Unfortunately, many marine equipment vendors are reluctant to share access even to the basic data generated by their machinery or choose to charge a data access fee that is considered to be excessive by ship owners.

Although several standards for machinery, performance and consumption data exchange were published over the last decade, they did not manage to get enough traction in the industry. This situation is often described as “isolated data silos”.

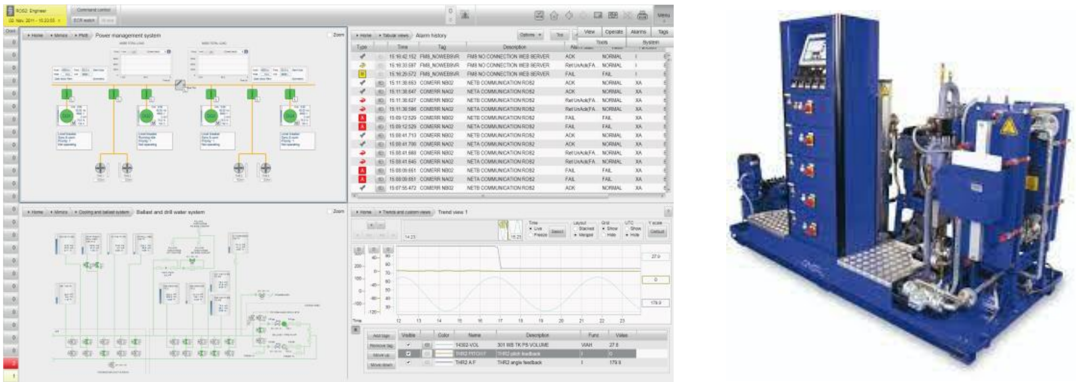


Fig.3: Digital machinery examples (Kongsberg AMS, Alfa Laval FCS)

While we are waiting for the OEMs to solve the problem of data silos and democratize access to the machinery data, a set of technologies were developed by EYEGAUGE and other technological companies that can be used to extract data locked in digital equipment in a non-invasive way. We will leave those solutions outside of the scope of this paper and assume that data from onboard digital equipment can be extracted.

4.1. Consumption monitoring of analog flow meters

Since volumetric flowmeters are currently the most widespread in maritime transportation, we will focus on data collection from them. Certain models of volumetric flowmeters available on the market are equipped with digital (Modbus) or analog (pulse or 4-20 loop) interfaces that can be easily connected to auto logging equipment. Some of those models are also equipped with a temperature probe and can transmit the FO temperature as well. Specific gravity must still be entered manually by the crew, however.

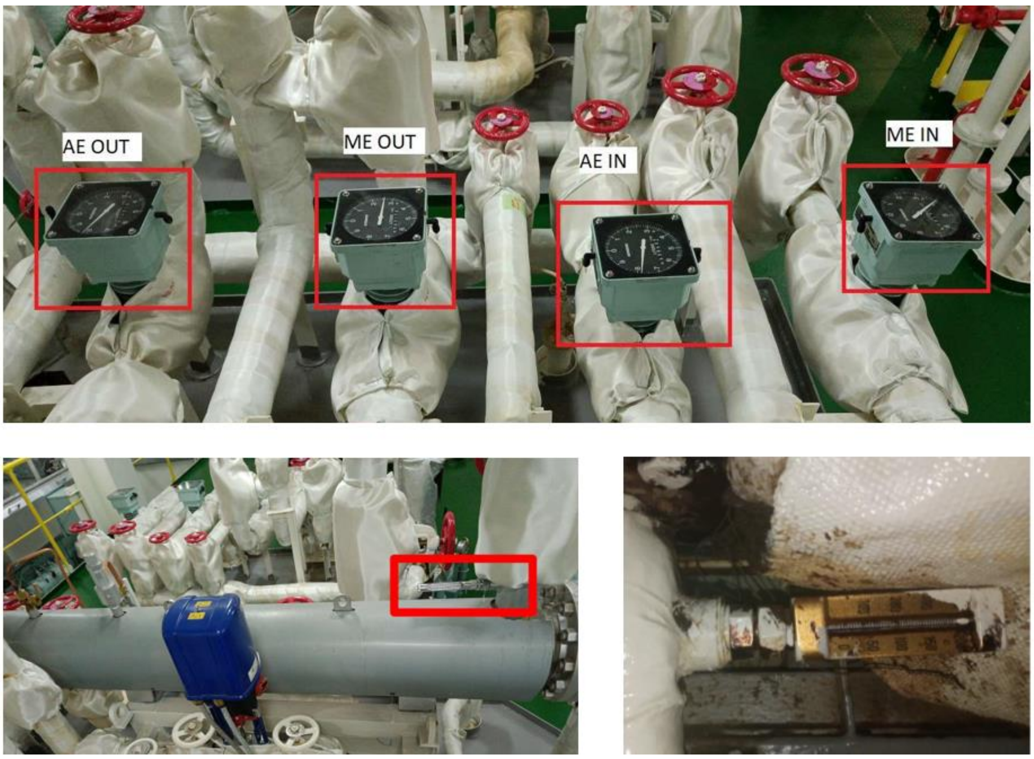


Fig. 4: Examples of onboard analogue volumetric flowmeters and FO thermometers

Unfortunately, more often, even onboard recently built vessels, we find the most basic flowmeters with mechanical, or LCD displays used in combination with standalone “mercury type” thermometers, Fig.4. Often those instruments are located in difficult to access areas and are sometimes found in neglected condition.

As we can see, volumetric flow meters are the best candidates for automated data collection using smart cameras. The accuracy of the collected data will be close to the accuracy of the flow meter itself and the accuracy (and state) of the corresponding FO thermometer.

For the setup we will use a set of cameras positioned in front of every FO flowmeter and FO thermometer, Fig.5. If some flowmeters and thermometers are located close to each other, a single camera can collect data from multiple instruments.

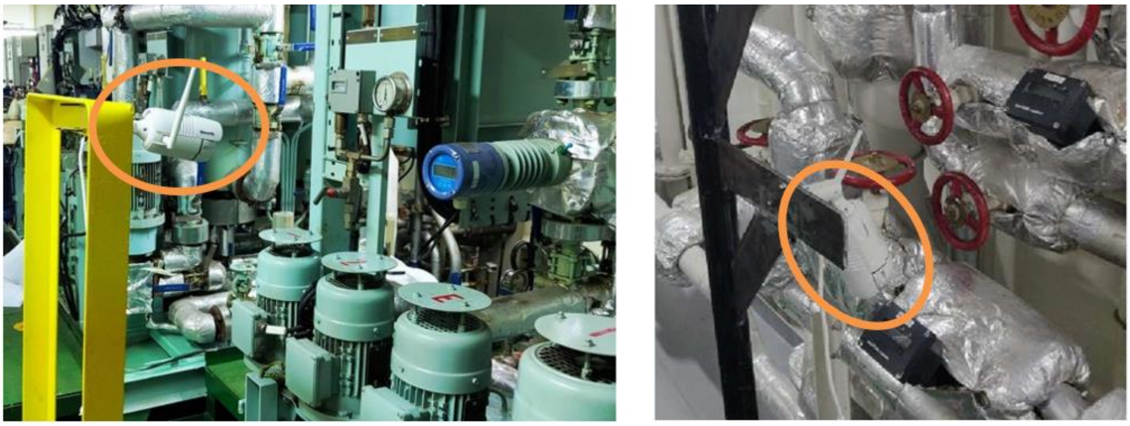


Fig.5: Positioning of cameras for consumption monitoring

This type of data collection requires us to specify the frequency at which we need to receive data. Although ISO 19030 recommends a 15 s (0.07 Hz) sampling rate, the commonly accepted sampling period is between 5 and 15 minutes. In our study we will use 10 minutes because ISO 19030:2 recommends splitting higher frequency sampling into 10 minutes blocks.

For conversion from volume (liters) to mass (MT), we need first to calculate fuel density (Rt1) and will use the *JIS (1989)* standard:

```
Rt1 = Rt0 – C * (t1 – t0)
M = V * Rt1

Where
       Rt1:   Specific Gravity
       Rt0:   Specific Gravity at 15/4 °C
       C:     Correction coefficient 0.00065 (heavy fuel oil)
       t1:    Measured temperature
       t0:    15 °C
       V:     Measured volumetric flow
       M:     Mass flow
```

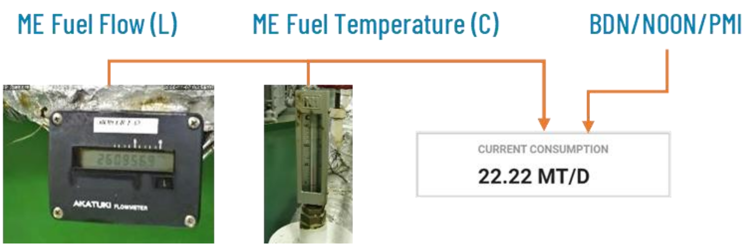


Fig.6: Mass flow calculations from volumetric flow, temperature, and FO parameters

Specific fuel gravity depends on the actual fuel used and must be updated on each fuel change from a bunker delivery note or a lab test. This information can be input manually by the crew (e.g. via means of a noon report or a BDN), or, for electronically controlled engines, it can be automatically retrieved from the main engine PMI system.

Unfortunately, it is not possible to find ships with both volumetric and mass flow meters installed, therefore, to evaluate the efficiency of this method of data collection, we will compare the daily consumption reported by the crew in noon reports with our calculations summed up over 24 h, Fig.7. Here we have sample data from 1 year monitoring of ME consumption of a 63 000 DWT bulk carrier using the described auto logging method from analogue volumetric flowmeters and thermometers versus consumption data reported by the crew via noon reports.

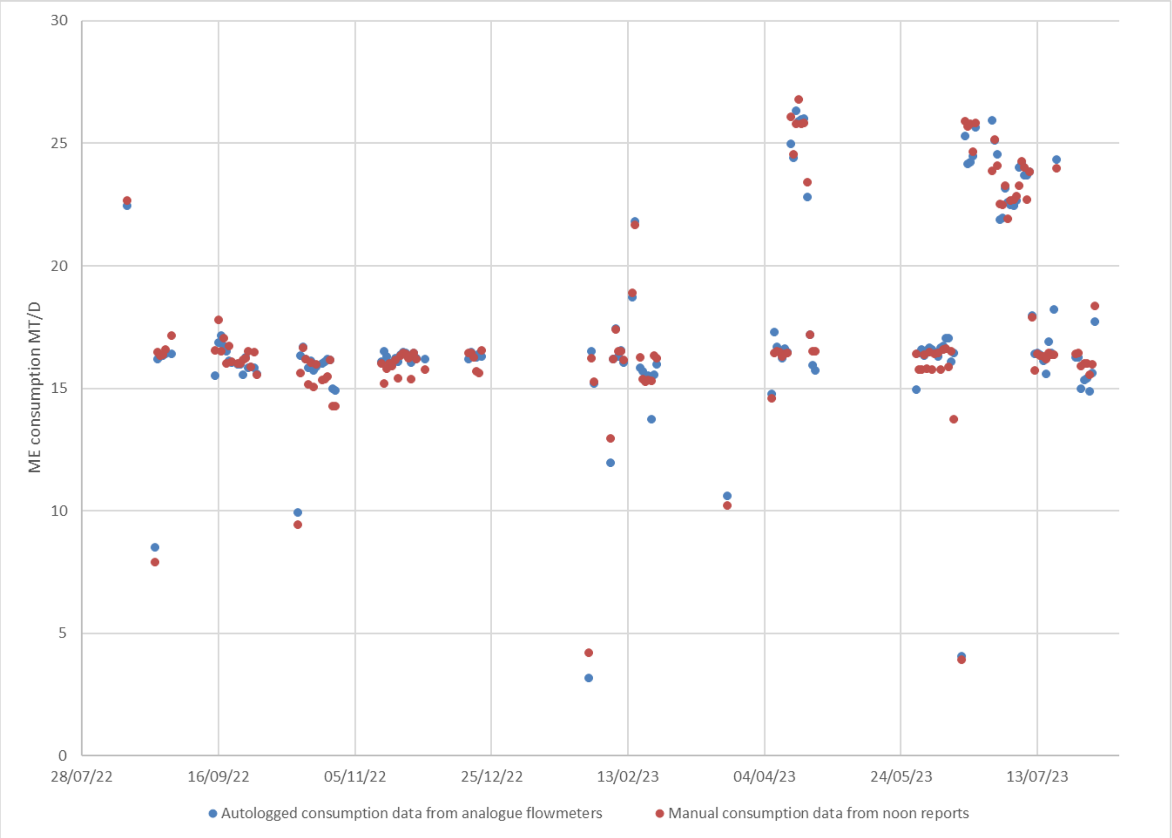


Fig.7: Comparing automated consumption monitoring to noon report data

We can observe a mean absolute percentage error (MAPE) of 2% with a mean absolute error (MAE) of 0.45. As you can see this result is very close to the accuracy of the volumetric flowmeter itself.

4.2. Performance monitoring of electronically controlled engines

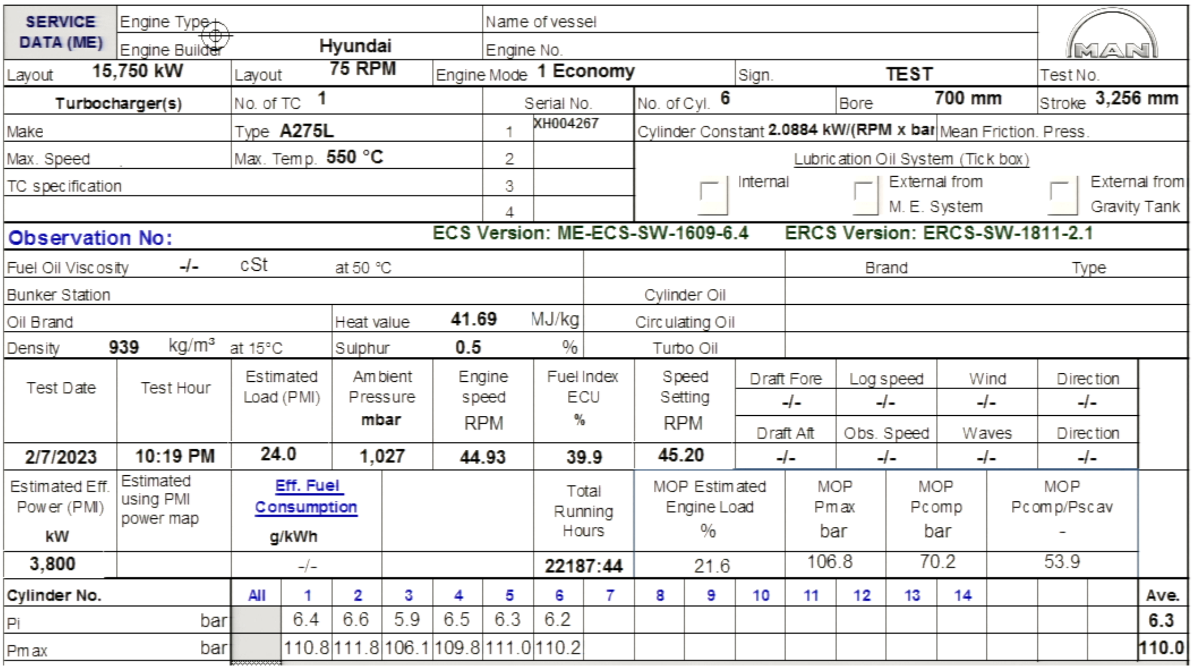
As it was mentioned in section 2.2, for two-stroke engines directly coupled to propeller (no gearbox) without shaft generator the engine power can be used as an approximation of the delivered power.

Electronically controlled engines such as two-stroke MAN B&W ME series are equipped with individual cylinder pressure transmitters. Usually, such engines are supplied with online performance monitoring systems, such as MAN PMI (Performance Measurement Indicator), https://man-es.com/docs/default-source/document-sync/performance-measurement-indicator-eng.pdf, that are able to automatically estimate the engine power, *Berdempe (2020).*

The calculation is performed according to the following formula, MAN (from the Instruction Book Operation for 50-108MC/MC-C Engines):

```
Pme = Pmi - K
Pe = C x Pme x Ne x Z

Where
Pmi:   Mean indicated cylinder pressure (bar)
Pme:   Mean effective pressure (bar)
Pe:    Effective power (in kW)
K:     Mean friction pressure loss (engine mechanical efficiency is generally
       independent of the engine load and is usually accepted as 1 bar)
C:     Cylinder constant (determined by the dimensions of the engine)
Ne:    Main engine speed
Z:     Number of cylinders
```



SERVICE DATA (ME)	Engine Type		Name of vessel		MAN
	Engine Builder	Hyundai	Engine No.		
Layout 15,750 kW	Layout 75 RPM	Engine Mode 1 Economy	Sign. TEST		Test No.
Turbocharger(s)	No. of TC 1	Serial No.	No. of Cyl. 6	Bore 700 mm	Stroke 3,256 mm
Make	Type A275L	1 XH004267	Cylinder Constant 2.0884 kW/(RPM x bar)		Mean Friction. Press.
Max. Speed	Max. Temp. 550 °C	2	Lubrication Oil System (Tick box)		
TC specification		3	Internal	External from M. E. System	External from Gravity Tank
		4			

Observation No: ECS Version: ME-ECS-SW-1609-6.4 ERCS Version: ERCS-SW-1811-2.1

Fuel Oil Viscosity -/- cSt at 50 °C			Brand	Type
Bunker Station		Cylinder Oil		
Oil Brand	Heat value 41.69 MJ/kg	Circulating Oil		
Density 939 kg/m³ at 15°C	Sulphur 0.5 %	Turbo Oil		

Test Date	Test Hour	Estimated Load (PMI)	Ambient Pressure mbar	Engine speed RPM	Fuel Index ECU %	Speed Setting RPM	Draft Fore / Draft Aft	Log speed / Obs. Speed	Wind / Waves	Direction / Direction
							-/-	-/-	-/-	-/-
2/7/2023	10:19 PM	24.0	1,027	44.93	39.9	45.20	-/-	-/-	-/-	-/-

Estimated Eff. Power (PMI) kW	Estimated using PMI power map	Eff. Fuel Consumption g/kWh	Total Running Hours	MOP Estimated Engine Load %	MOP Pmax bar	MOP Pcomp bar	MOP Pcomp/Pscav -
3,800		-/-	22187:44	21.6	106.8	70.2	53.9

Cylinder No.		All	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Ave.
Pi	bar		6.4	6.6	5.9	6.5	6.3	6.2									6.3
Pmax	bar		110.8	111.8	106.1	109.8	111.0	110.2									110.0

Fig8: Screenshot of MAN engine monitoring software

All the above parameters can be auto logged, and the data collection frequency will depend on the approach used to connect to the engine performance monitoring systems.

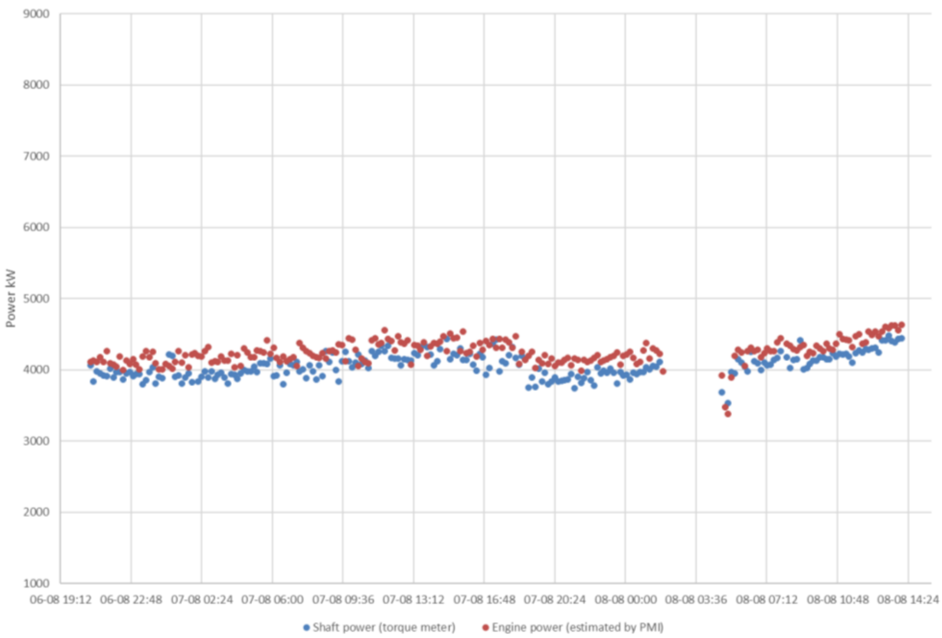


Fig. 9: Comparing engine power (from PMI) to shaft power for an electronically controlled engine

Fig.9 compares the calculated power with measurements of a shaft power meter installed on the same ship (81000 DWT bulk carrier with MAN 6S60ME-C8.2 8880 kW engine) over a single voyage. We can observe a mean absolute percentage error (MAPE) of 4.6%. As was already mentioned, due to the friction in thrust bearings the delivered (propeller) power will be lower than the engine power. From the above graph we can confirm the power loss. By simply shifting the estimated engine power by 180 kW we will get a MAPE of 1.8%.

4.3. Performance monitoring of mechanically controlled engines

Mechanically controlled engines such as two-stroke MAN B&W MC series are not generally equipped with online cylinder pressure transmitters and engine power can be calculated from fuel index (also known as fuel rack or pump mark) and RPM using power estimation curves found in ship trials documentation.

Most often the power estimation curve for a particular engine may provide directly the Pme (mean effective pressure) that can be transformed into effective engine power using formula from section 4.2, Fig.10, or it can be based a more sophisticated calculation that takes into account the fuel oil parameters such as type, density, and temperature, Fig.11.

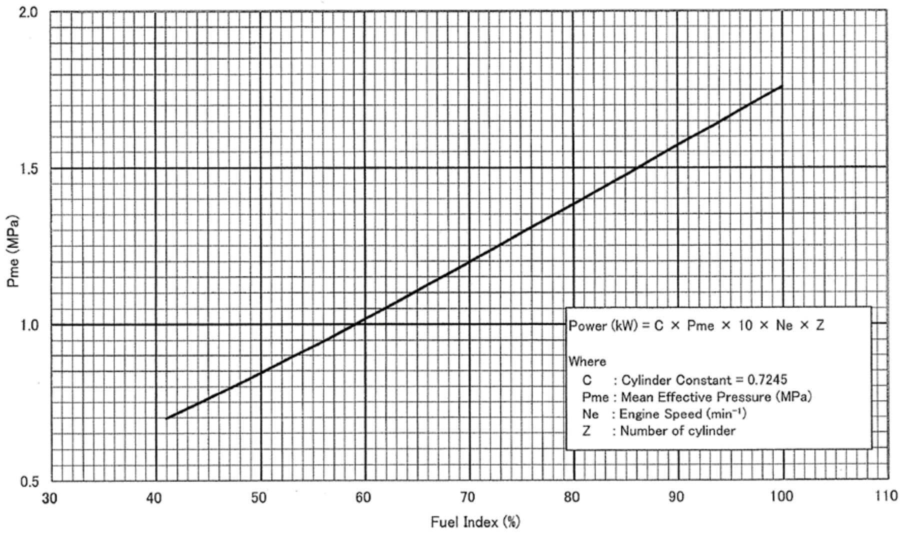


Fig. 10: Power estimation curve example (Pme only)

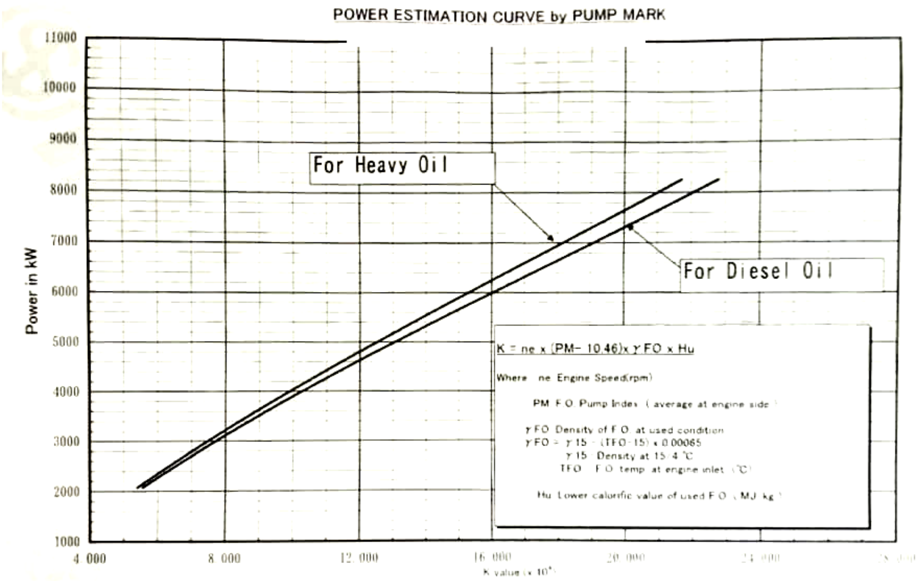


Fig. 11: Power estimation curve example (with FO parameters)

The above method of power estimation from fuel index has 2 issues:

- performance curves are influenced by engine degradation and accumulate error over time;
- mechanically controlled engines rarely have digital interfaces suitable for automated data collection and are designed to be monitored manually by the crew.

While it is quite challenging to update performance curves regularly, we can address the problem of automated data collection with the camera-based approach proposed in section 3.1.

With a single camera placed in the ECR in front of the Main Engine console we can collect RPM and Fuel Index data at the required frequency and estimate the engine power in real time.

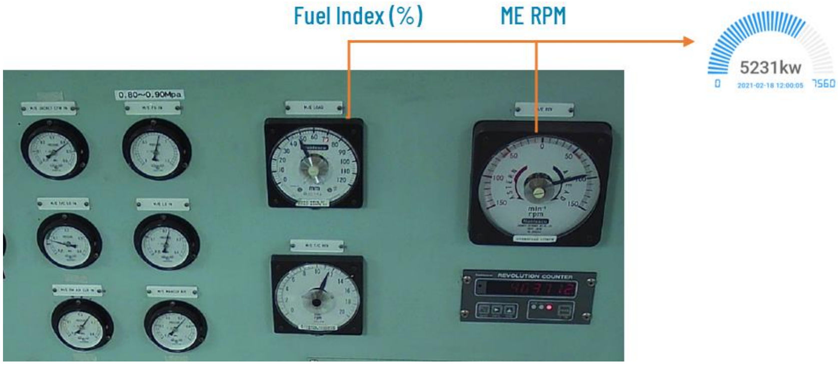


Fig. 12: Live monitoring and calculation of engine power on MC engines

If the performance curve for the particular engine requires fuel parameters (e.g. specific gravity and calorific value), those parameters can be obtained in the same way as discussed in section 4.1 for volumetric flowmeters.

Fig.13 compares the calculated power with the measurements of a shaft power meter installed on the same ship (61000 DWT bulk carrier with MAN 6S50MC-C8 8260 kW engine) over a single voyage.

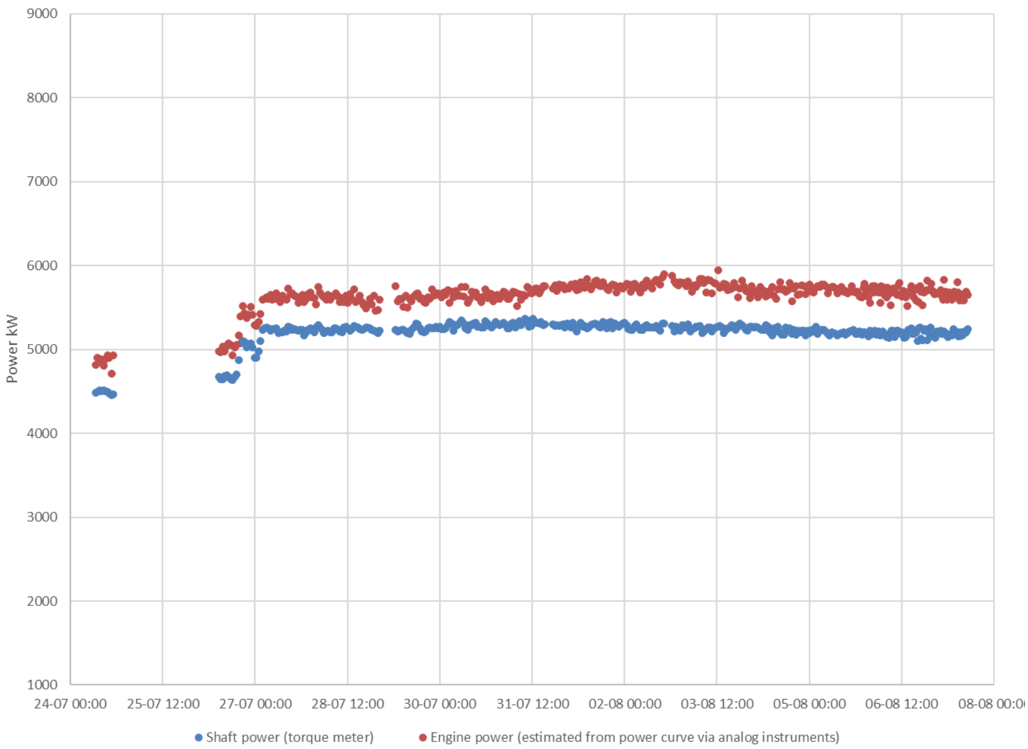


Fig.13: Comparing engine power to shaft power

Note that similar to electronically controlled engines, due to the friction in thrust bearings, the delivered (propeller) power will be lower than the engine power. And here we see a very strong separation of two measurement types. We can observe a mean absolute percentage error (MAPE) of 8%. By shifting the estimated engine power by 350 kW we will get a MAPE of 1.2%.

5. Conclusion

In this paper we presented alternative approaches to automated high-frequency ship performance and consumption data collection that do not require replacement of existing flow meters and installation of torque meters. These non-invasive approaches make data driven performance optimization more accessible to ship owners and charterers.

The proposed method for monitoring of fuel oil consumption from analog volumetric flow meters provides data quality close to human monitoring but at high frequency and is only limited to the accuracy of the existing fuel flow flowmeters and thermometers. For ship performance monitoring we have shown the ways to automatically collect and estimate engine performance data for both electronically and mechanically controlled engines. The obtained results were compared to propeller power data collected by a torque meter and showed a mean absolute percentage error (MAPE) between 4.6 and 8% with a stable bias explainable by a power loss on thrust bearings. With a simple adjustment in calculations compensating for this power loss it is possible to get very close to the level of data quality expected by the ISO 19030 standard of ship performance monitoring.

Acknowledgement

The author and the EYEGAUGE team would like to express their gratitude to MC Shipping, Cargill Ocean Transportation, SaftetyTech accelerator and crews for their participation and feedback.

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The Value of Autolog Performance Monitoring for an Owner

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Abstract

The purpose of this paper is to present real-life examples of benefits bringing autolog performance data to shore and available online. The examples are based on more than 100 vessel years high frequency data collection. The paper will furthermore demonstrate the needed initiatives with focus on cost, installation, and integration both of data but also among staff and crew. Among the benefits, the EEOI development over seven years will be presented clearly demonstrating the potential efficiency gains compared with annual market rates. Furthermore, the paper will argue for the need of high frequency data supporting the effort towards the maritime GHG emission limiting efficiency targets in 2030 via the Carbon Intensity Index (CII) as well as the forthcoming EU Emission Trading System (EU ETS) from 2024. Finally, the paper will present the auditors view on the future for more accurate high frequent data as well as data handling, not least for satisfying the expected need from stakeholders for transparency as well as documentation of GHG emission.

1. Introduction

The need for performance data has always been relevant for shipping companies but for a long time based on manual reporting – noon reporting – with one per day reported figure for consumption, draft, speed, position, cargo with few more. This level of data reporting was sufficient for a long time until the increase in fuel prices and the price for data transferring drop to a level where new online solutions became reachable cost wise.

The author will in this paper demonstrate the pathway from a pure noon reporting system to a full online performance system for the use of the company not only the technicians but operators, commercials, and management as well as the benefits.

Some of the periods described are before Ultragas and Navigator Gas merged in early 2021 so both owner names will be used in the paper. 'Operator/Operations' and 'Commercials' are used for the inhouse operational and commercial departments.

2. Early days

A shipping company is basically a logistic company carrying goods from A to B under different contracts, in liner- or spot voyages with a focus on the highest possible income. It will not be for this paper to explain and demonstrate the commercial functionality of shipping just to say that the purpose of the company as described above is what a performance system basically needs to support.

Furthermore, the climate and environmental focus with rather challenging goals needs more accurate data not least to develop a baseline but also for measure the development – or transition – towards the climate and environmental goals set.

During the early days the focus was solely on the fuel oil cost and ways to keep the cost down as well as describe the vessels speed and consumption in the most competitive way towards charters – although not with a too tight margin risking a contract dispute. If the vessel was on spot it will be operated by Owners with full control of the speed and consumption, but on a charter party operated fully by charters. So, if the vessel was not on a spot voyage the incentives for reducing fuel oil cost by efficient operations were few unless the vessel could not perform in accordance with a contract.

Noon reporting was the tool to report the one per day performance of the vessel. The inaccuracy of the data was rather high but acceptable, covered by the contract performance margins.

In connection with the strive towards higher crew welfare, better and stronger data coverage was one of the tools. The price per kB decreased to a level where data picked up onboard could be rather cheaply transferred to a server ashore. This made the way for a higher level of data transferring soon followed by new equipment installed onboard like mass flow meters, torsion meters, power meters and various sensors. The installation package where costly and the benefit a bit blur as seen from the commercial side, but slowly the benefit would be revealed and supported by all.

Ultragas made investments back in 2013 installing mass flow meters (on main engine) and torsion meters on seven LPG/c newbuildings as a kind of a pilot to get a better idea of the potential benefits from overviewing the main engine- and hull performance at different drafts and speeds. The speed- and speed log sensors were of a normal make which later showed to be with a high inaccuracy although acceptable due the high number of incoming autolog data.

2.1. Description of installations

Ultragas installed mass flow meters in the fuel oil system at in- and return main, shaft torsion meter and power meters for the auxiliary engines all connected to a Marorka server installed in the cargo control room. A few years later mass flow meters (in- and return) were installed in the auxiliary engines fuel oil system and mass flow meter at inlet to the oil-fired boiler. Furthermore, connections were made to the cargo system as well as the vessels navigational system.

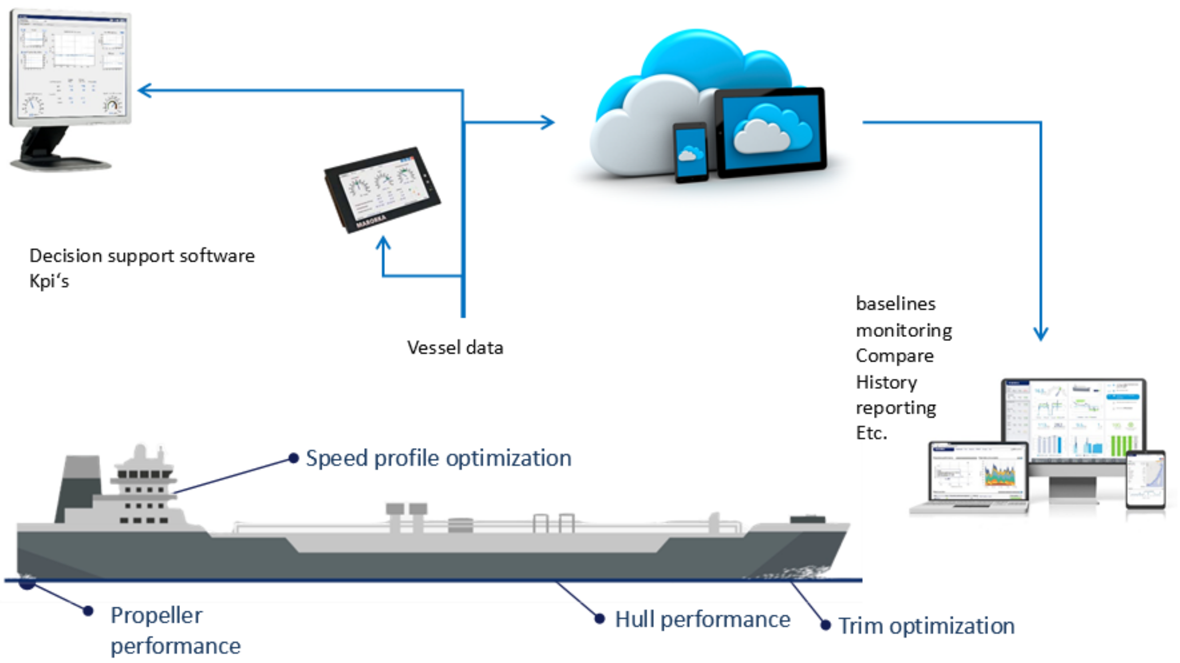


Fig.1: Early set up of autolog performance system (source: Marorka)

This gave Ultragas the possibility to collect, transfer and report following data:

- Main- and aux engines consumption, power, SFOC and running hours
- Oil fires boiler consumption and running hours
- Position, heading, speed (log & GPS), draft, trim and wind
- Shaft power/torque and rpm
- Rudder angle
- Cargo weight, temperature and pressure per cargo tank

The data can be collected down to a few seconds per reading, but it was decided to bring it home in 15-minute packages to reduce some of the fluctuations seen.

The installation budget was estimated at USD 50-60,000 per vessel although logistics and unforeseen situations somewhat increased the cost slightly.

2.2. Early findings – hull efficiency ballast vs laden

Bringing data home reveals the inaccuracy of the many original onboard sensors, especially the speed logs and draft sensor but also the noon reported consumption (which were still reported in parallel) versus mass flow meters. This led to some crew discussions regarding the accuracy of mass flow meters and to a lesser degree the feeling of being monitored from shore. Both topics are relevant and need to be addressed and dealt with as the success of the changes is through proper communication and cooperation not least between crews and shore staff.

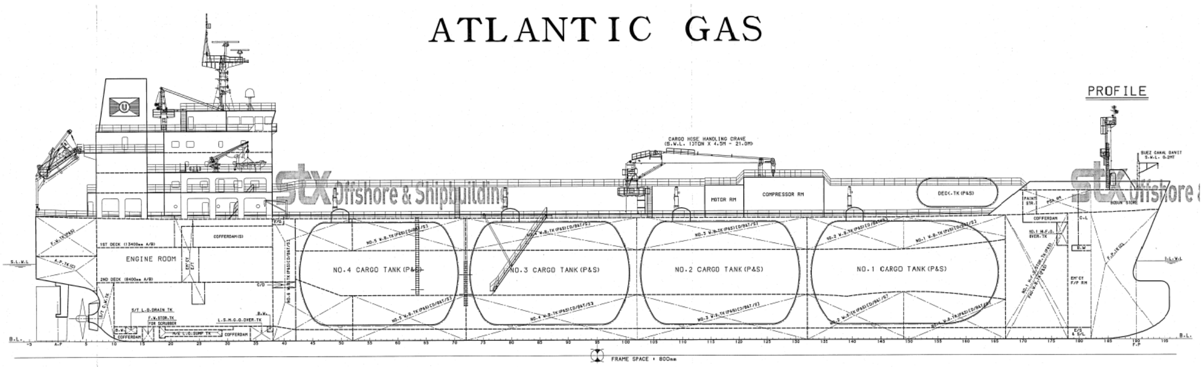


Fig.2: Typical LPG/c design – incl. Mewis duct and pronounced bulbous bow

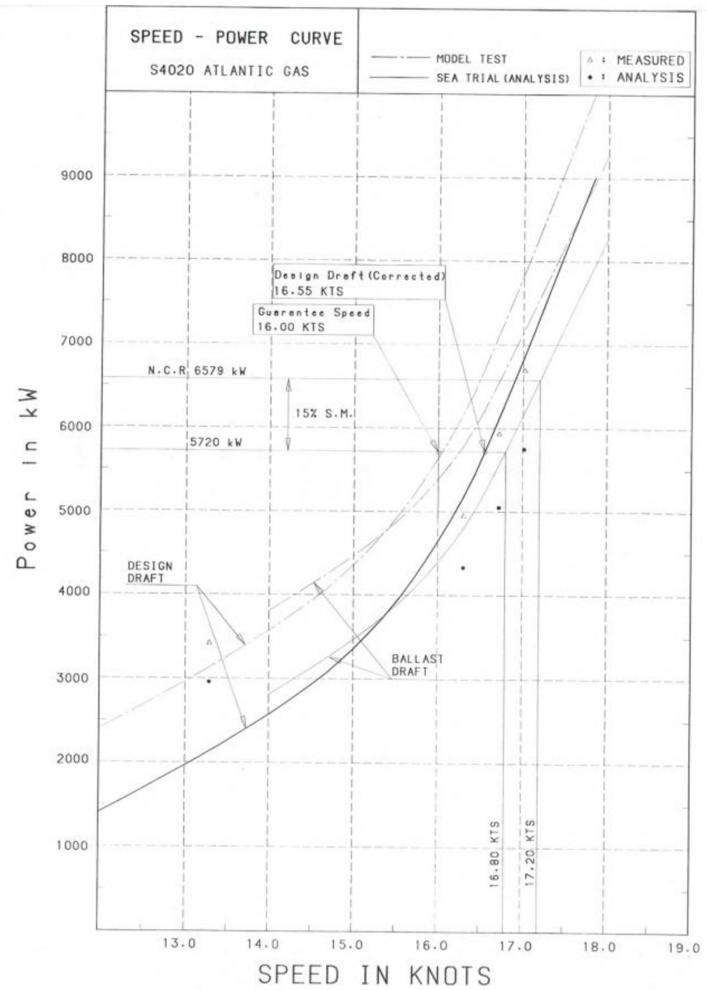


Fig.3: Sea trial results ballast & design – light ballast drafts penalized the performance

The early learning was the rather small difference between ballast and laden draft due to the vessel's hull design with a pronounced bulbous bow optimized for the design draft and an installed propeller wake improvement duct also designed for design draft - a typical LPG/c design for the time.

Furthermore, the typical ballast condition was light with a pronounced aft trim which made the bulbous bow inefficient and in certain conditions penalizing the hull efficiency. And most likely caused an increased inefficiency of the propeller wake improvement duct although we cannot for certain prove it as all seven vessels are delivered with a duct.

Just as a remark, the typical LPG/c hull design at the time where somewhat hampered with respect to hull efficiency by the focus on cargo intake in bi-lope tanks. This led to rather full body designs (high block coefficients) trading at design speeds of 16-16.5 knots, which is 1-2 knots faster than a typical tanker. Although, an LPG/c design is regarded as a "cubic" design and a tanker as "deadweight" design there are many similarities with tankers in the way it is designed.

It was clear from the new autolog data that the vessels where draft- and trim sensitive and highly designed for the design draft, Fig.3, and the vessels where guided to add more ballast (up to 2,000 tons in certain cases) and seek even keel as far as possible. But it was also recognized that the effect of trimming was dependable on speed, which led to further investments in a trim optimization tool.

2.3. Early findings – Trim optimization

Trim optimization is important for hull designs like LPG/c as the contract speed years ago were rather high and as such higher of today compared to tankers. A full body hull design at higher speeds is challenging to the designer leading to much focus on meeting the contract design speeds at the lowest power and consumption. If the Owner has not specified the operational profile (% in ballast, laden, partly loaded at a certain speed range) properly in the negotiated contract and specification, an optimized performance at design speed may be the result.

Therefore, it is important to understand the hull efficiency outside the design speed at a certain draft, which is why a trim optimization tool could be beneficial.

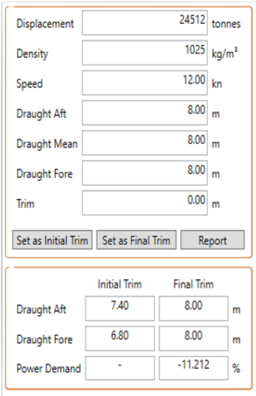
Ultragas decided to test the seven-vessel series in a model tank developing a trim optimization tool for the use of the crew and onshore performance department. The software SeaTrim©, Fig.4, from FORCE Technologies in Denmark was chosen as supplier.

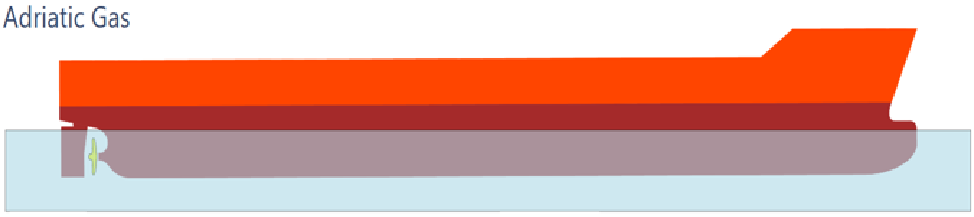
SeaTrim© was based on a matrix of 120 runs of resistance test with various trim, draft and speeds in the model tank and installed as independent software onboard the vessels and at shore.

The crew are planning their departure condition as normal and then input the condition in SeaTrim© checking for a more beneficial condition. A report will be forwarded to shore before departure. If there are changes to the speed and/or draft underway a new report will be made and forwarded to shore.

One example of the importance of mid-voyage trim optimization is the example as described below, Fig.5. During an eastward Pacific crossing to Panama fuel oil was transferred from the forward fuel oil tank to aft - approximately 100 m - changing the trim from 7.3 m even keel to 7.0/7.6 aft trim. Not much of a change but resulted in a staggering 25% increase in consumption and CO_2 emissions. The change in trim causing the rather high increase in consumption was clearly seen from the autolog data, Fig.5.

This example shows the importance of checking the performance in case the speed and/or trim are changed. However, it must be said that the average savings from trim optimization on these vessels are about 5-8% in ballast and up to 5% in laden. The benefit will be less and less visual in line with the crew experience increases.





Aft — Trim[m] — Fore

Draught$_{Mean}$[m]

[%]	1.80	1.60	1.40	1.20	1.00	0.80	0.60	0.40	0.20	0.00	-0.20	-0.40	-0.60	-0.80	-1.00	-1.20
6.80	20.08	21.05	22.02	22.99	23.95	24.91	25.88	24.59	23.30	22.01						
7.00	21.83	21.90	21.97	22.05	22.29	22.53	22.77	21.63	20.50	19.36						
7.20	23.57	22.75	21.93	21.11	20.63	20.14	19.66	18.68	17.70	16.72						
7.40	25.32	23.60	21.89	20.17	18.97	17.76	16.55	15.73	14.90	14.08						
7.60	27.06	24.45	21.84	19.23	17.30	15.37	13.44	12.77	12.11	11.44						
7.80	28.81	25.30	21.80	18.30	15.64	12.99	10.33	9.82	9.31	8.79						
8.00	29.05	25.21	21.38	17.55	14.71	11.87	9.03	8.56	8.09	7.62	6.57	5.51	4.45	2.62	0.79	-1.04
8.20	27.78	24.18	20.59	16.99	14.50	12.01	9.53	8.99	8.46	7.93	7.08	6.24	5.39	3.94	2.49	1.04
8.40	26.51	23.15	19.79	16.43	14.30	12.16	10.02	9.43	8.83	8.23	7.60	6.96	6.33	5.25	4.18	3.11
8.60	25.25	22.12	19.00	15.88	14.09	12.31	10.52	9.86	9.20	8.54	8.11	7.69	7.26	6.57	5.88	5.19
8.80	23.98	21.09	18.21	15.32	13.89	12.45	11.02	10.29	9.57	8.84	8.63	8.41	8.20	7.89	7.58	7.26
9.00	22.71	20.06	17.41	14.76	13.68	12.60	11.52	10.73	9.94	9.15	9.14	9.14	9.13	9.20	9.27	9.34
9.20	22.06	19.84	17.63	15.42	14.38	13.34	12.30	11.78	11.26	10.74	10.81	10.88	10.95	10.90	10.86	10.82
9.40	21.40	19.63	17.85	16.08	15.08	14.08	13.08	12.83	12.58	12.33	12.48	12.62	12.76	12.61	12.45	12.29
9.60	20.75	19.41	18.07	16.74	15.78	14.82	13.86	13.88	13.90	13.93	14.14	14.36	14.58	14.31	14.04	13.77
9.80	20.09	19.19	18.30	17.40	16.48	15.56	14.64	14.93	15.23	15.52	15.81	16.10	16.39	16.01	15.63	15.25
10.00	19.44	18.98	18.52	18.05	17.18	16.30	15.42	15.99	16.55	17.11	17.48	17.84	18.20	17.71	17.22	16.72
10.20	20.94	20.78	20.63	20.48	19.49	18.50	17.52	18.22	18.92	19.62	19.43	19.25	19.06	18.99	18.91	18.83
10.40	22.43	22.59	22.75	22.91	21.81	20.71	19.61	20.45	21.29	22.13	21.39	20.66	19.92	20.26	20.60	20.95
10.60	23.93	24.40	24.86	25.33	24.12	22.91	21.70	22.68	23.66	24.64	23.35	22.07	20.78	21.54	22.30	23.06
10.80	25.42	26.20	26.98	27.76	26.44	25.11	23.79	24.91	26.03	27.14	25.31	23.47	21.64	22.81	23.99	25.17

Fig.4: Typical screen dump from SeaTrim©

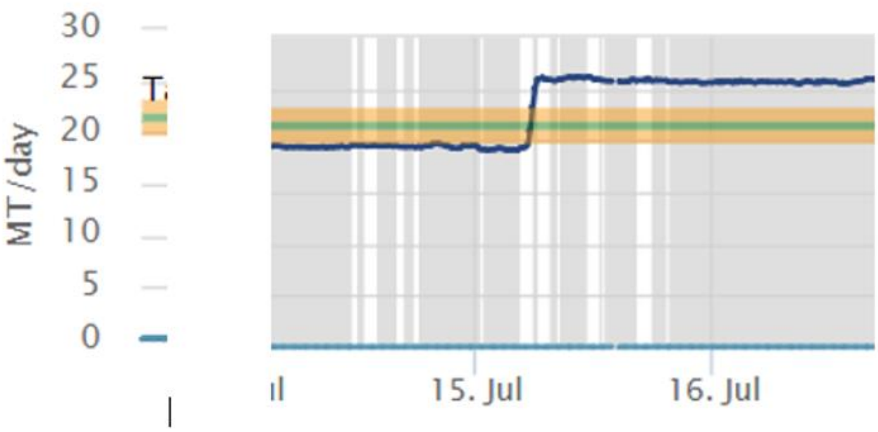


Fig.5: Increase of consumption due to fuel oil shifting from forward to aft increasing aft trim

2.4. Early findings – added resistance and fouling

The choice of anti-fouling coating is, as all know, an important part of the performance improving strategy. Choosing the correct fouling depends on cost, expected idle time, operation time and speed and what seems to be a correct choice at one point can be changed with the market, the need for speed and change of idle time.

Based on autolog data we could visualize that contract/voyages with a high profit could change to a poor result if the added fouling resistance from the longer idle periods were included.

One example is a vessel on a charter (externally operated) with a vague hull cleaning clause resulting in limited overview of added resistance due to fouling and the need of cleaning.

Autolog data revealed an over-consumption of more than 20% but no cleaning was performed by the charters resulting in an over-consumption of 215 tons fuel oil in 30 days compared to a daily consumption of about 20 tons. When the vessel was re-delivered back to Ultragas the performance was poor and beyond recovery until next dry dock, Fig.6.

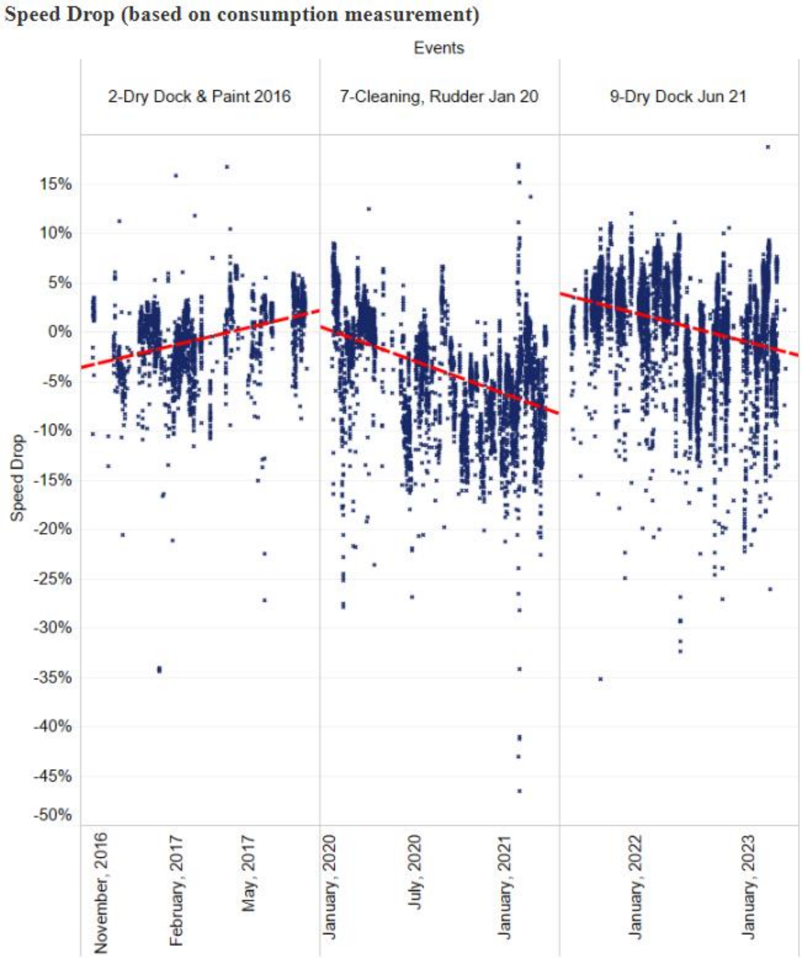


Fig.6: Consequence on performance from increased idling and lack of cleaning

Fig.6 shows the change in speed drop over time since delivery from the newbuilding yard in 2016. The first year shows a decrease in speed drop due to self-polishing abilities by the anti-fouling paint which is somewhat expected and a steady performance until 2020 where the vessel entered the mentioned one-year charter contract resulting in a speed drop of almost 10% (equals about 25% increase in consumption). The anti-fouling was beyond recovery by cleaning and the vessel was rather poor performing until she was docked late 2021 costing about ½ million dollars in added fuel oil cost.

2.5. Early findings – optimized running of aux engines and oil-fired boiler

The auxiliary engines on an LPG/c have normally a max output of 20-25% compared to the max output of the main engine and up to 45% for a ethylene carrier. The energy for cargo cooling, purification, purging and machinery- and cargo handling is produced by the auxiliary engines which makes them an important consumer. The oil-fired boiler is basically used for heavy fuel oil heating with more and is not regarded as an important consumer.

During design of a vessel engine layout based on expected electrical balance it is often seen that the auxiliary engines are the same in size most likely because it is easier/cheaper for the yard to manage three similar auxiliary engines compared to variations in models and size. It is however important that the Owner focuses on the variance in the electrical balance loads for different scenarios, not least for gas carriers, to ensure that at least one engine is optimized in size for handling the hotel load. This will be beneficial for consumption as well as running hours. And which is why Ultragas installed power meters in the main switchboards for the auxiliary engines to overview and optimize the auxiliary engines running hours and consumption.

It was soon discovered that the hotel load could not be handled by one auxiliary engine resulting that a second engine kicking in, Fig.7. From Fig.7 it is clear that after a long period of cooling covered by two auxiliary engines and stopped around noon 20th July the auxiliary engines continued to run even though the power needed could be well covered by one auxiliary engine. This could be caused by either the automatic management system being switched to manual or sat at a lower max output than 85% MCR for one engine. The low load running triggered an alert after 6 hours of running forwarded automatically by mail to the technical superintendent.

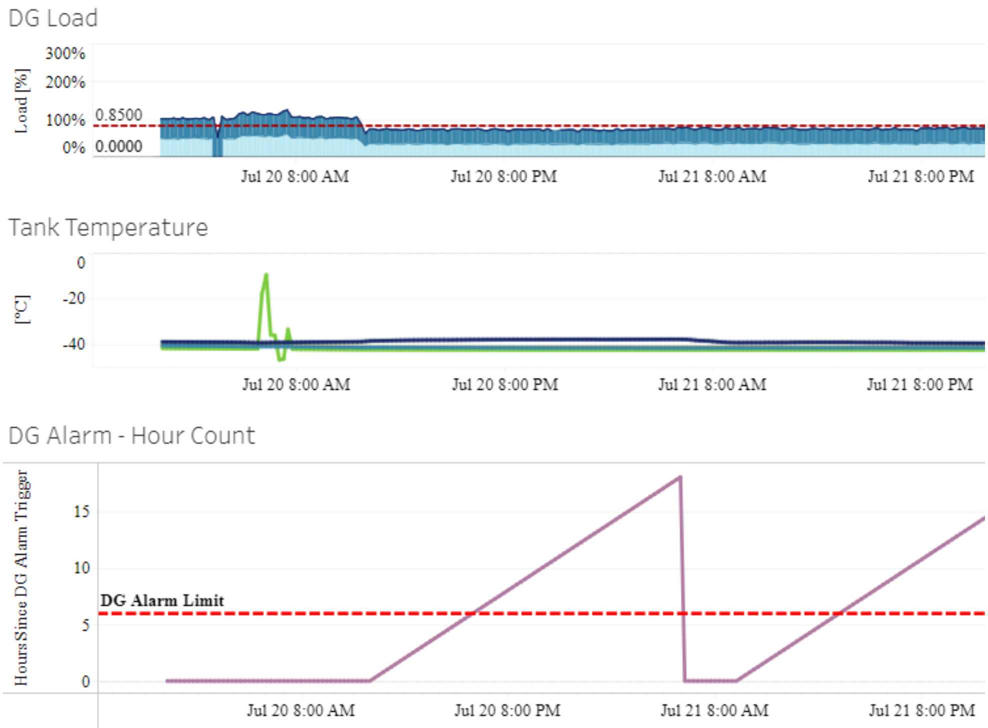


Fig.7: Two diesel generators running at low load (< 85%MCR of one)

The oil-fired boiler has a less significant role to play, and its consumption is somewhat overlooked. The consumption per day operative equals less than 1% of the total consumption however still worth of chasing. As seen from Fig.8 the oil-fired boiler is running even though the main engine exhaust boiler produces enough steam. The boiler consumption is not very high but still worth reducing as well as the running hours.

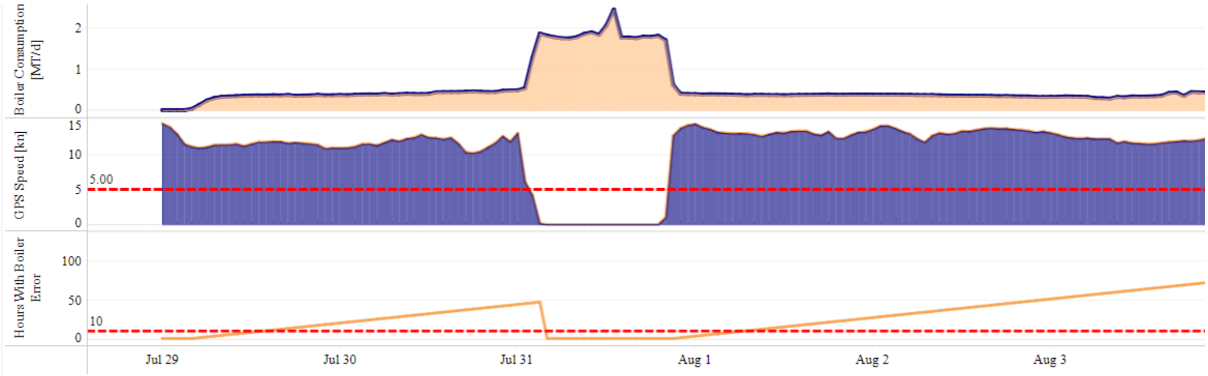


Fig.8: Oil-fired boiler running when main engine is in operation

The annual over-consumption from auxiliary engines and the oil-fired boiler is estimated to 2-2.5% of the total consumption and about 12-15% of the total consumption by auxiliary engines and boiler.

2.6. Early findings – optimized cargo cooling

As mentioned, energy for cargo cooling is significant and every cargo cooling enroute is well planned to reach the cargo terminal at the agreed cargo temperature otherwise penalized by cargo owner.

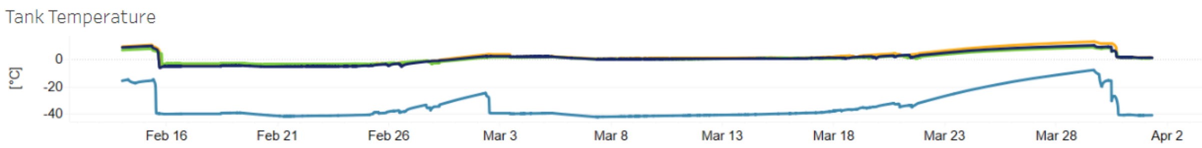
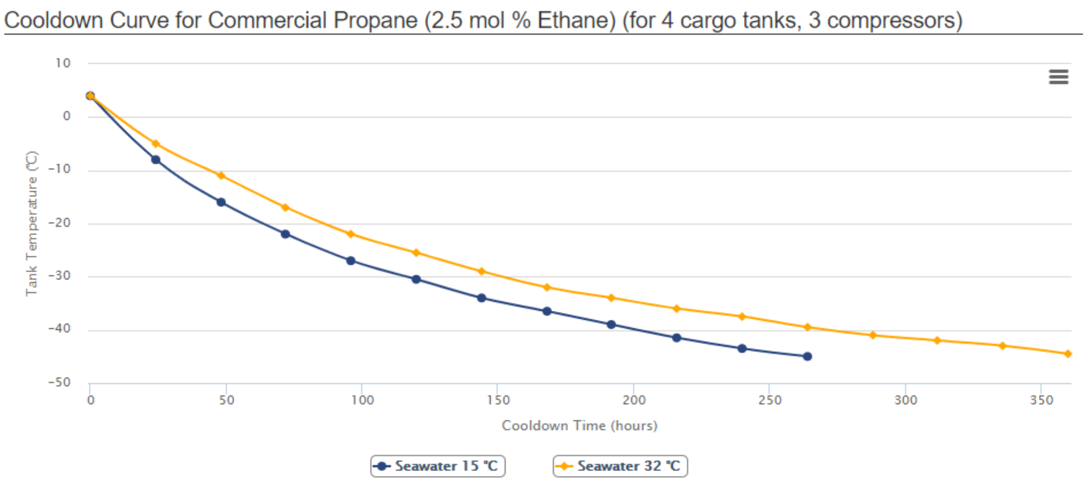


Fig.9: Cargo cooling for a full voyage



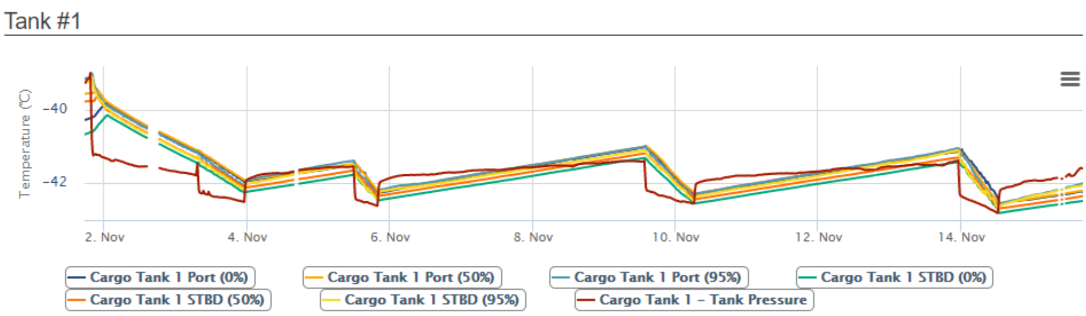


Fig. 9A Standard cooling and correct cooling strategy during longer laden voyages

Even though Ultragas experienced a variance in cooling methods by the onboard gas engineer from vessel to vessel the dominant way of cooling was to cool down to expected discharge temperature during the full voyage which is not the most optimized way of performing cargo cooling, Fig.9. Fig.9 shows a rapid cooling at the beginning of the voyage which is kept during the full voyage until late March. An optimized way of performing cooling during a voyage would be a gradual cooling over time and enroute just ending in the expected temperature for discharge, Fig.9A. Therefore, standard cooling curves for various cargoes were integrated in the vessel performance system for easy tracking by operation of the cargo cooling performance.

2.7. Early findings – auxiliary equipment

It was decided quite early in the process to apply frequency controlling systems to cooling pumps and main engine room blowers to limit the energy used. This was decided after an onboard energy review inspection by an external consultant pointing out areas for improvement hereunder increased insulation, Fig.10, of fuel oil- and steam pipes. Furthermore, LED lighting was introduced in the engine room. All together the energy consumption was reduced slightly, but the hotel load was still at a level where the second auxiliary engine was kicking in.

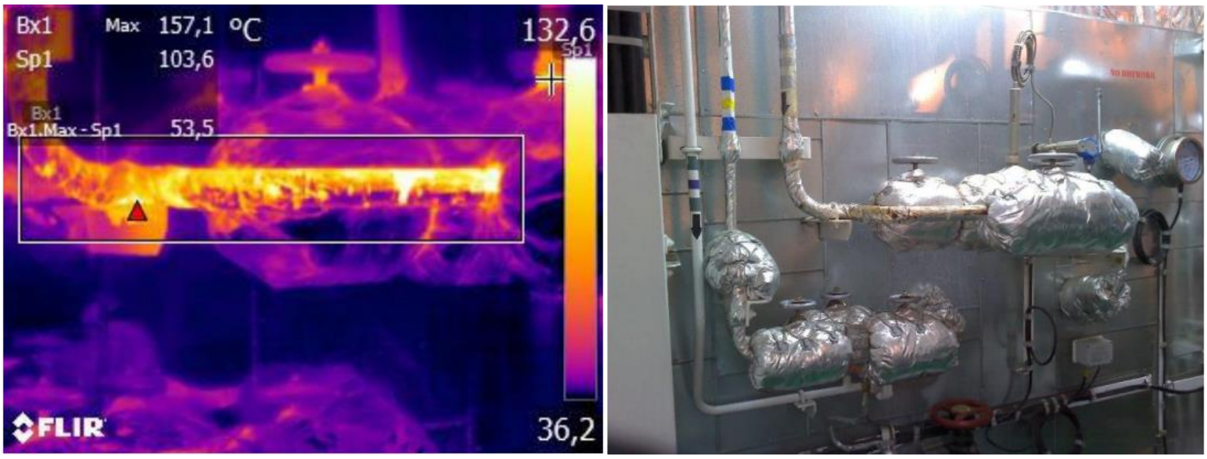


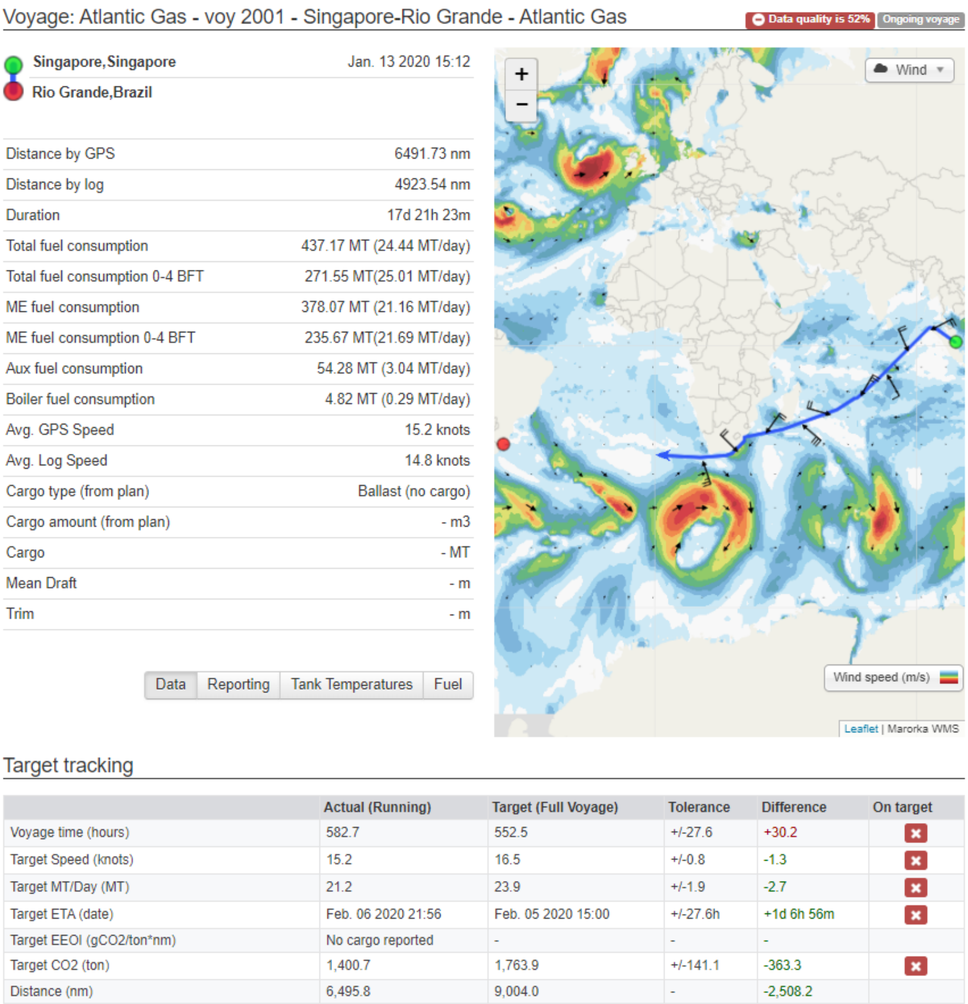
Fig.10: Thermically pictures of non-insulated fuel oil system

2.8. Early findings – awareness and alert settings

A vessel performance system does not save a penny if not used! A slogan which is equally truth today as well as in the past. Therefore, training and awareness is of great importance and should have the highest and continuous priority.

By having a performance system installed the speed and consumption could be visualized vessel by vessel and not based on vessel class. The speed and consumption were in Ultragas the same for the whole sister class with no real consideration to actual performance of the individual vessels which was changed by introducing the vessel performance system.

A voyage tool was introduced to the Operator, Fig.11, filled out before start of the voyage and goals (traffic light) checked during the voyage. The goals with +/- tolerance were set by the commercials and operators and both under- and over performing would be presented as a red traffic light. Key targets were consumption per day, ETA and speed where main target in a low market was consumption and speed/ETA in high market. Alerts are triggered if the traffic lights (consumption) are red for a certain time and forwarded to the operator responsible for the voyage. The operator will then decide if the targets for the voyage should be altered and if so, re-enter the new targets into the system. The new targets will immediately be visible onboard on a screen on the bridge, Fig.13. The detailed performance of the voyage is available for the operator, Fig.12, including weather to give the operator a better understanding of the conditions the vessel is in.



Distance by GPS	6491.73 nm
Distance by log	4923.54 nm
Duration	17d 21h 23m
Total fuel consumption	437.17 MT (24.44 MT/day)
Total fuel consumption 0-4 BFT	271.55 MT(25.01 MT/day)
ME fuel consumption	378.07 MT (21.16 MT/day)
ME fuel consumption 0-4 BFT	235.67 MT(21.69 MT/day)
Aux fuel consumption	54.28 MT (3.04 MT/day)
Boiler fuel consumption	4.82 MT (0.29 MT/day)
Avg. GPS Speed	15.2 knots
Avg. Log Speed	14.8 knots
Cargo type (from plan)	Ballast (no cargo)
Cargo amount (from plan)	- m3
Cargo	- MT
Mean Draft	- m
Trim	- m

	Actual (Running)	Target (Full Voyage)	Tolerance	Difference	On target
Voyage time (hours)	582.7	552.5	+/-27.6	+30.2	✖
Target Speed (knots)	15.2	16.5	+/-0.8	-1.3	✖
Target MT/Day (MT)	21.2	23.9	+/-1.9	-2.7	✖
Target ETA (date)	Feb. 06 2020 21:56	Feb. 05 2020 15:00	+/-27.6h	+1d 6h 56m	✖
Target EEOI (gCO2/ton*nm)	No cargo reported	-	-	-	
Target CO2 (ton)	1,400.7	1,763.9	+/-141.1	-363.3	✖
Distance (nm)	6,495.8	9,004.0	-	-2,508.2	

Fig.11: A typical voyage overview – for the Operator and checked daily

Fig.12: Voyage overview of consumption, speed (log & GPS), shaft rpm, wind speed and current. The shaded areas are time with wind > BF4

A monthly review of the voyages was performed, and it was soon discovered that the speed and consumption profiling of the vessels in the commercial system (used by the commercials) were not aligned with the actual performance of the specific vessel. Therefore, a quarterly review of the vessels' speed and consumption data, Fig.13, was established, and the commercial system updated if needed.

The updated performance data including margins was distributed to the operator for the use of planning future voyages, Fig..14).

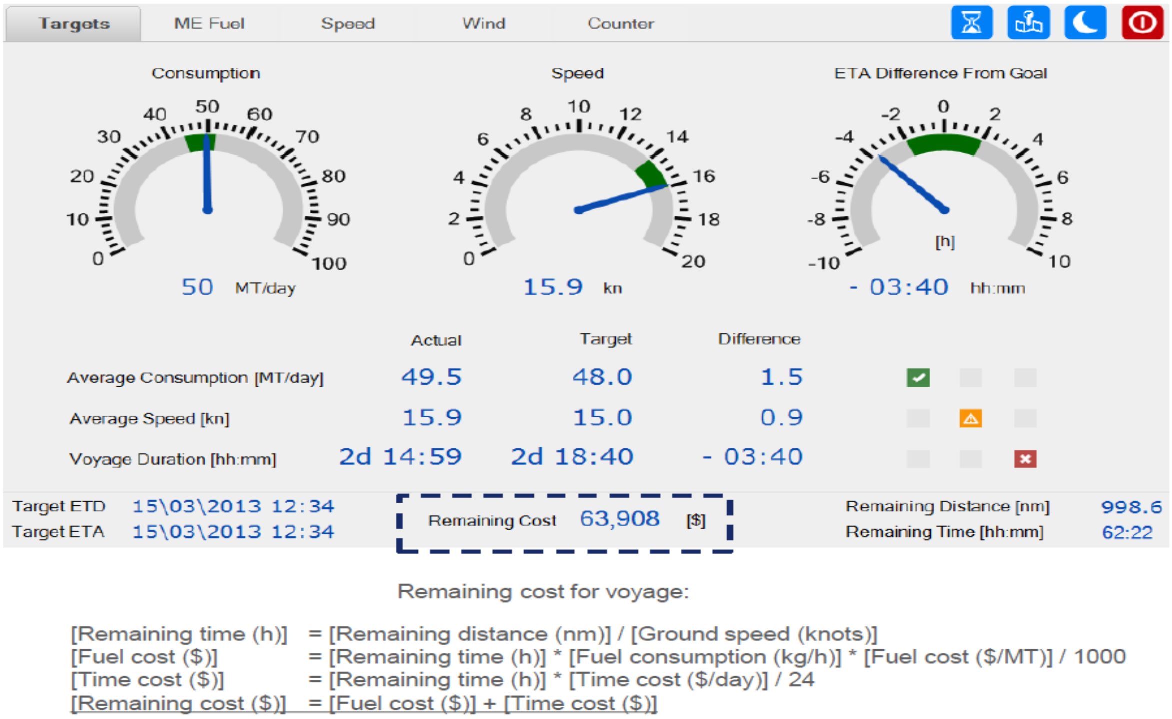


Fig.12: Viewer on vessels bridge showing targets for the specific voyage

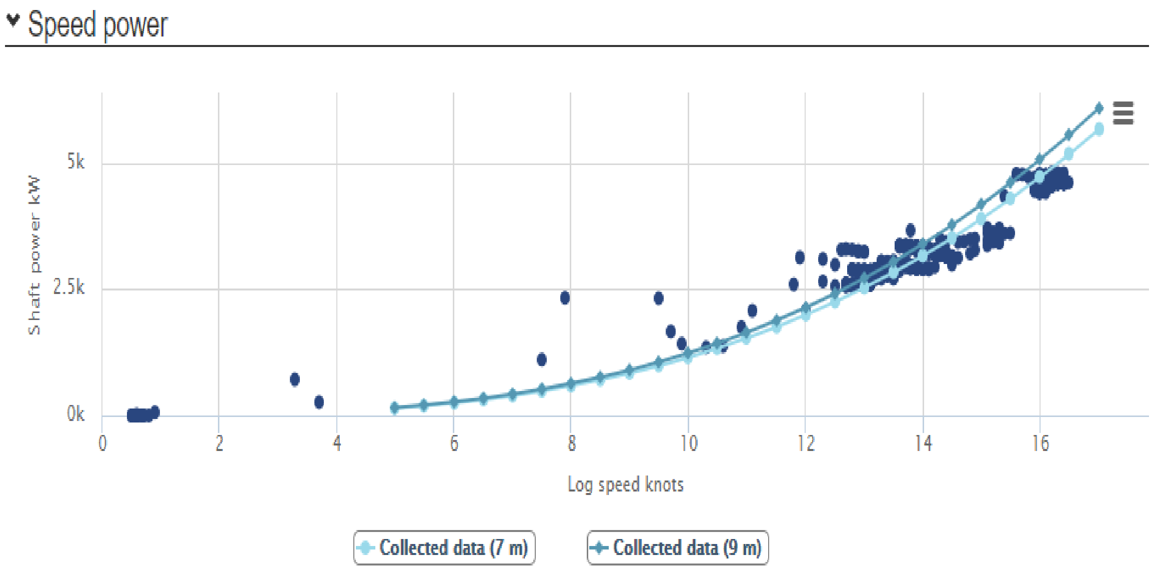


Fig.13: Actual good weather performance vs standard ballast- & laden curves

The above-mentioned sounds easy and logical but it means that office staff need to change their daily duties, which were regarded as add-ons to their daily work. Therefore, it was quite important to train and explain why the extra work was important and demonstrate the benefit to the bottom line.

In the early days we experienced some good and not so good examples of voyage management performance, which is demonstrated below, Fig.14A and B. In Fig.14A there have been no review of the voyage and the vessels arrive late at a high consumption across Atlantic Ocean most likely due unfavorable weather conditions. The consequence is overconsumption and somewhat unexpected late arrival. If discovered early during the voyage the operator/commercial could have discussed the terms and condition for late arrival and possible slow down saving fuel. The fuel penalty was an over-consumption of almost 80 tons fuel close to 4 days of normal consumption during a 10-day voyage.

	Ballast Baseline Consumption [MT/d]	Laden Baseline Consumption [MT/d]
10.0	5.1	7.4
10.5	5.8	8.4
11.0	6.6	9.5
11.5	7.5	10.6
12.0	8.5	11.9
12.5	9.5	13.2
13.0	10.6	14.6
13.5	11.7	16.1
14.0	13.0	17.7
14.5	14.3	19.3
15.0	15.7	21.1
15.5	17.2	23.0
16.0	18.8	24.9
16.5	20.5	27.0

Fig.14: Vessel specific speed and consumption table for the use by the operator

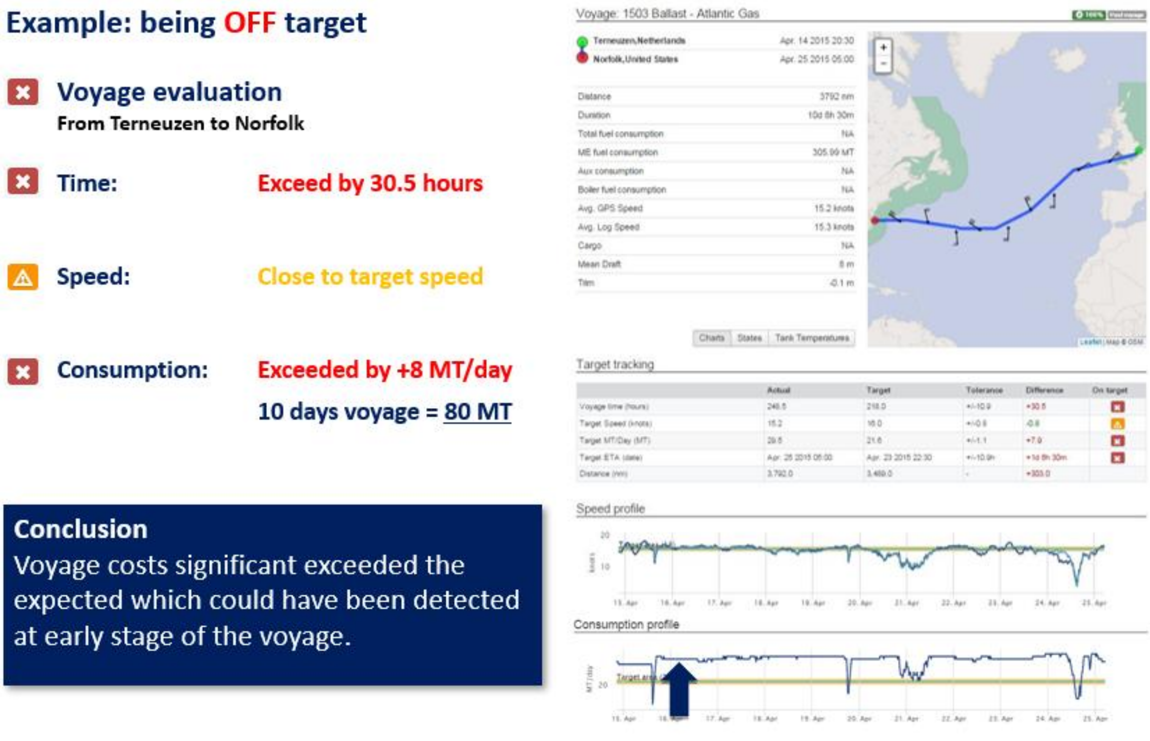


Fig.14A: The consequences of being off voyage target

Even though the weather has been less favorable than expected a cooperation between the vessel crew and the operator resulted in an optimum performance during an Atlantic Ocean crossing, benefiting the voyage commercial result, Fig.14B.

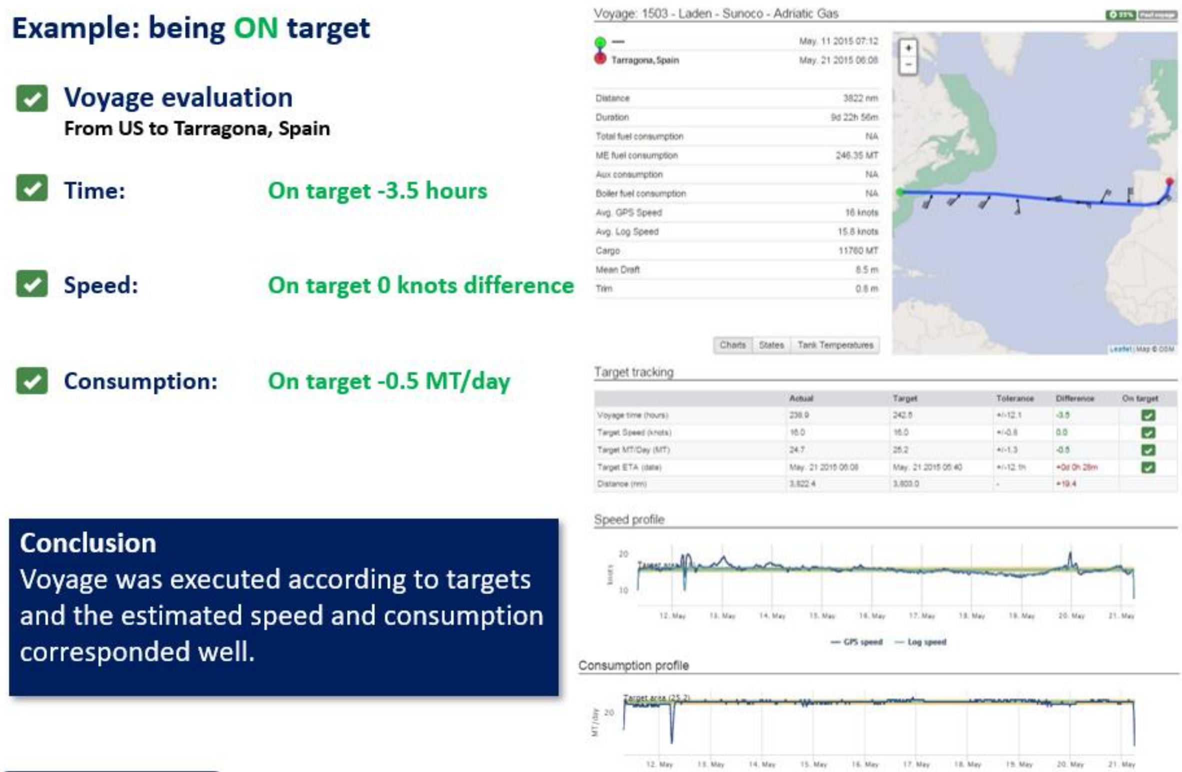


Fig.14B: The consequences of being on voyage target

2.9. Early findings – results and conclusions

Navigator Gas has not yet found the perfect energy performance measure for what we are doing. There are several measures available like CII, EEOI with more but we do not find that they cover the areas which in we would like to measure ourselves.

Fig. 15 EEOI development vs monthly rates since start of autolog

It was found important to combine technical performance with a commercial figure to understand how efficiently we move one ton of cargo a certain distance with special focus on CO_2 emissions. It was decided to use EEOI + average monthly rates as the need for speed (and thereby consumption) varies with market demand – and therefore the rates, Fig.15.

Since the start of autolog EEOI has decreased more than 30% irrespective of the development on the market which means that the fleet is more efficiently traded than before the autolog installation. It shows that all the efforts made and focused performance and awareness has paid off. This can also be seen on the development of CII where the seven sister vessels are currently all in A or B although the CII is not the most perfect measure of efficiency.

3. Current efforts and way ahead

It is without doubt that better and more accurate data is needed for the shipping industry to demonstrate and verify the energy used and GHG emitted. Accurate noon reporting may be sufficient for some, but it is clear to us that validated autolog data is necessary for demonstrating further efficiency initiatives as well as quantify the emission to an accuracy level where our customers and regulative bodies are satisfied. When EU ETS and FuelEU Maritime kicks in there will be a cost on CO_2 as well as need for fuel mix demonstration which will be audited pushing autolog data in a central role. After the early days with autolog experience in Ultragas it was decided to extend the installations to more vessels. Ultragas was merged with Navigator Gas in 2021 and the installation program was extended to the full fleet of 55 vessels and is still ongoing. Currently, there are 30 vessels fully equipped with performance systems collecting data as described in 2.1 and we expect the full fleet will be equipped by the end of 2024.

3.1. Current efforts and way ahead – commercial efficiency

What is commercial efficiency when it comes to performance? The commercial system is basically where the commercials calculate the main figures for a future voyage with output such as daily rate, speed, ETA with more. In the past the vessels' performance where normally described as a group of sisters in the commercial systems resulting in large consumption margins to cover the most inefficient vessel among the sisters. This could be accepted if the consumption was not more than the market would expect. When the contract was signed, and the vessel lived up to the promised performance there were no real incentives to perform more efficiently. However, this was not the case for the so-called spot voyages where the fuel was paid by the Owner and consumption tried minimized.

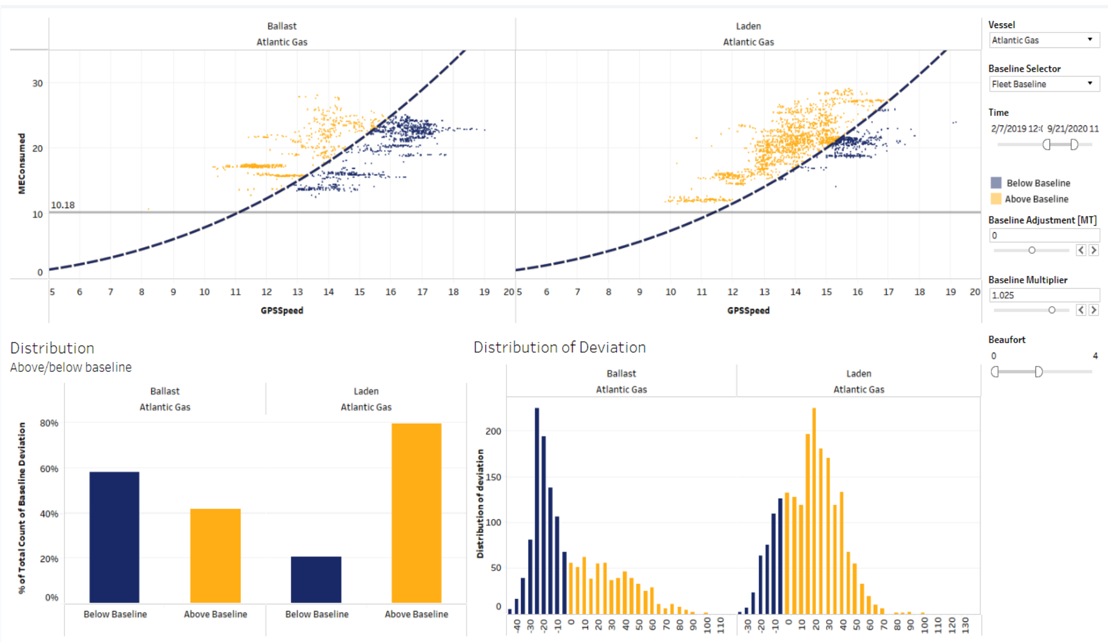


Fig.16: Charter Party prognosis based on actual performance

As the vessels with autolog were no longer described as a group but individually in the commercial systems we had a chance to optimize the performance and be more competitive when closing contracts with cargo owners. However, when you want to be more precise and limit the speed and consumption margin you may have the risk of under performance during a charter voyage or arrive late on a spot voyage. So, how to quantify the risk of under performance when lowering the consumption margins?

A tool was made based on autolog data where we could adjust the consumption margins and weather and get a picture of the likelihood of being above the margin input. Therefore, it was quite easy to adjust the margins to an acceptable commercial level which in many cases were significantly below the normal margin used in the past.

3.2. Current efforts and way ahead – Monthly reports & awareness

In the past and before autolog the technical manager was instructed to perform a diver inspection every 6 months to understand the level of hull and propeller fouling. This was not always done due to commercial and technical reasons and was in some cases not done. And in some cases, the vessel was greatly under performing for a long period before the fouling was discovered.

This was changed after the introduction of autolog as the vessel's performance was overviewed day by day and summarized in monthly reports presented to the operation and commercials, Fig.17.

Ship Name	Hull coating & fuel saving devices	Data Quality. Past 6 months	Latest Hull & Prop. Performance.	GPS Speed [kn]	Docking cons. at 12.5 and 15kn (load	Last 4 months consumption at 12.5 and 15kn (loaded)	Last 4 months avg. propulsion consumption % increase @ loaded condition @ months after docking	Comments
Adriatic Gas		AVG.	POOR	12.5 15	11.5 18	NA 22.5	25% after 45 months	Torque meter faulty. Warranty case (SUPPORT-28237). Propeller polished on 28 April 2023. 7 % improvement in hull performance.
Arctic Gas		GOOD	GOOD	12.5 15	11.5 18	11.2 18.9	4% after 20 months	Idled between 21 April to 25 May of Abidjan. Idling again since 9 July ongoing. Anti-fouling should still be functioning.
Atlantic Gas		POOR	NA	12.5 15	11.5 18	12.4 20.8	NA% after 45 months	New torque meter power readings are missing since 27 June and before was 20% lower compared to sister vessels (SUPPORT-28269). ME Consumed is frozen since 10 June. She was idling in Red Sea since 27 June. Hull and propeller performance can be anything.
Balearic Gas		GOOD	NA	12.5 15	11.5 18	NA NA	NA% after 40 months	Idling from March to May in Philadelphia US. Hull performance can be anything after such a long idling time. Torque meter not reading. Propulsion consumption readings frozen.
Bering Gas		AVG.	GOOD	12.5 15	11.5 18	11.3 18.9	5% after 25 months	No concern. From the shaft power readings, it doesn't indicate any issue with the hull since last docking. The main engine flow meter was calibrated, but consumption is slightly higher than expected. Prop. polished 2023-05-02. Good improvement in hull performance for now. Good voyage management between 15 to 20 July with extreme weather.
Celtic Gas		GOOD	AVG.	12.5 15	11.5 18	12.1 20.3	11% after 40 months	Propeller polished 2023-01-04.
Pacific Gas		GOOD	AVG.	12.5 15	11.5 18	12.3 20.8	15% after 44 months	Forward draft sensor is reading higher drafts values, than expected. Analysis change to take only aft draft readings and the vessel hasn't been loading with distinct loaded and ballast drafts last few voyages. Propeller polishing recommended.

Fig.17: Monthly report – sister vessels

Past 5 month's fuel table - Laden [Good weather data]

Confidence level in table: REASONABLE

Average Speed kn	Main Engine Power Mean draft = 9m [kW]	Main Engine RPM Mean draft = 9m [rpm]	Main Engine Consumption Mean draft = 9m [MT/day]
9	1717	70	7.7
10	1813	72	8.1
11	2101	75	9.3
12	2480	79	10.9
13	3015	84	13.2
14	3471	88	15.2
15	4094	93	18
16	4679	97	20.7
17	5413	101	24.2

Past 5 month's fuel table - Ballast [Good weather data]

Average Speed kn	Main Engine Power Mean draft = 4.7m [kW]	Main Engine RPM Mean draft = 4.7m [rpm]	Main Engine Consumption Mean draft = 4.7m [MT/day]
9	1522	68	6.9
10	1620	69	7.3
11	1886	73	8.4
12	2244	77	9.9
13	2714	81	11.9
14	3130	85	13.7
15	3696	90	16.2
16	4247	94	18.7
17	4912	99	21.8

Fig.18: Speed and consumption data – past five months and in good weather (<BF 4)

The experience from the increased awareness between the technical management and operations on the hull and propeller fouling has been positive as it can be seen on the overall performance. Furthermore, we no longer have unnecessary hull cleanings with wear and tear on the anti-fouling coating as a result.

The speed and consumption input to our commercial systems is updated every six months or after dry docking and in some cases after hull cleaning. The data input is based on last five months autolog data, Fig.18.

3.3. Current efforts and way ahead – anti-fouling strategy

It did not take a long time after installing autolog onboard before we realized that the anti-fouling coating applied did not match the operational profile of the vessels where longer idle time in warm waters was not unusual. It was clear that longer idle periods resulted in lack in anti-fouling self-polishing, increasing the need for more frequent hull cleanings, leading to even lower performance over time, Fig.19.

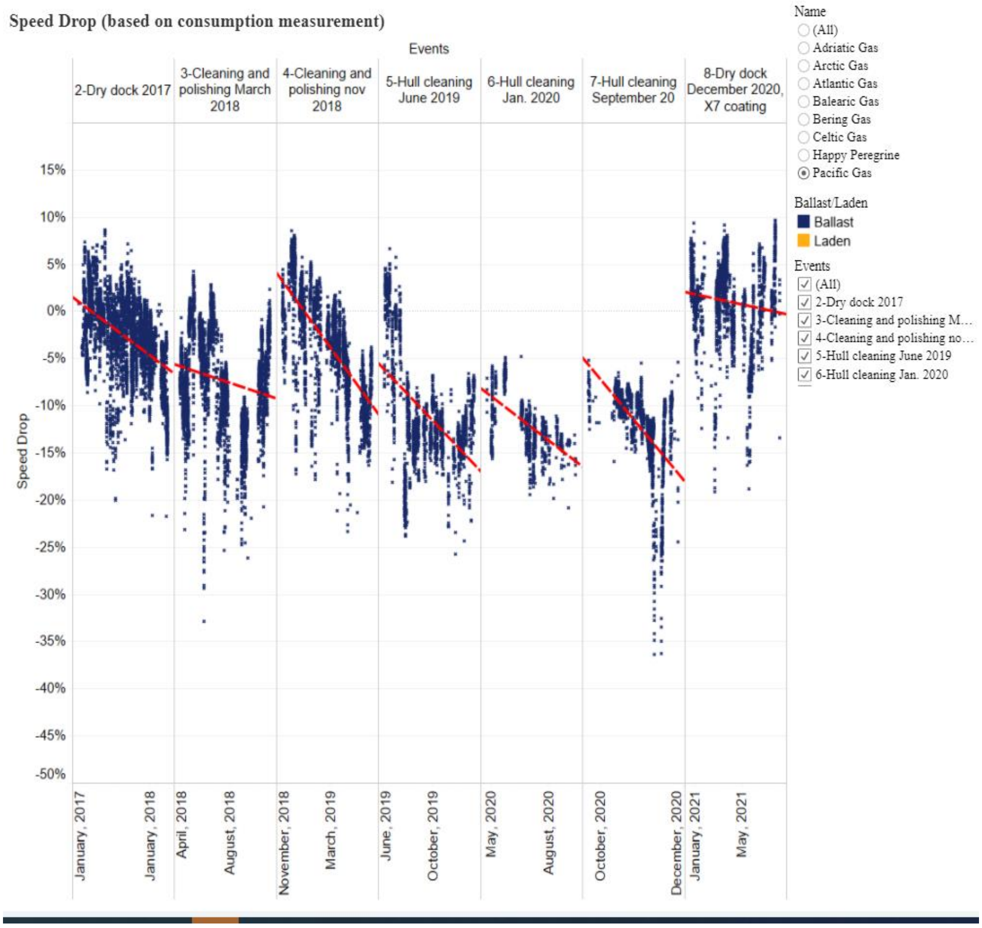


Fig.19: Speed drop over a period of four years until new anti-fouling was introduced

The speed drop after longer idle periods observed was surprisingly high and the time for the anti-fouling system to regain efficiency longer and seldom back to the starting point. Therefore, it was decided to change anti-fouling system during scheduled dry docking to a system that was more resistant to idle periods. The effect can be seen on the speed drop in figure 19. The fuel oil and savings and the reduction of CO_2 emissions have been significant for the fleet to an extent where we have decided to use similar anti-fouling systems for all vessels when dry docking.

Furthermore, we are investigating if advanced dry docking just for applying new anti-fouling could be beneficial even for vessels outside the dry-docking period.

3.5. Current efforts and way ahead – Weather Routing

Weather routing is normally ordered from voyage-to-voyage from different providers and the vessel is then guided externally by the provider. It has long been a wish from our side to integrate voyage planning with weather routing in the same performance system and new initiatives have commenced and been launched on trial basis (see fig. 20).

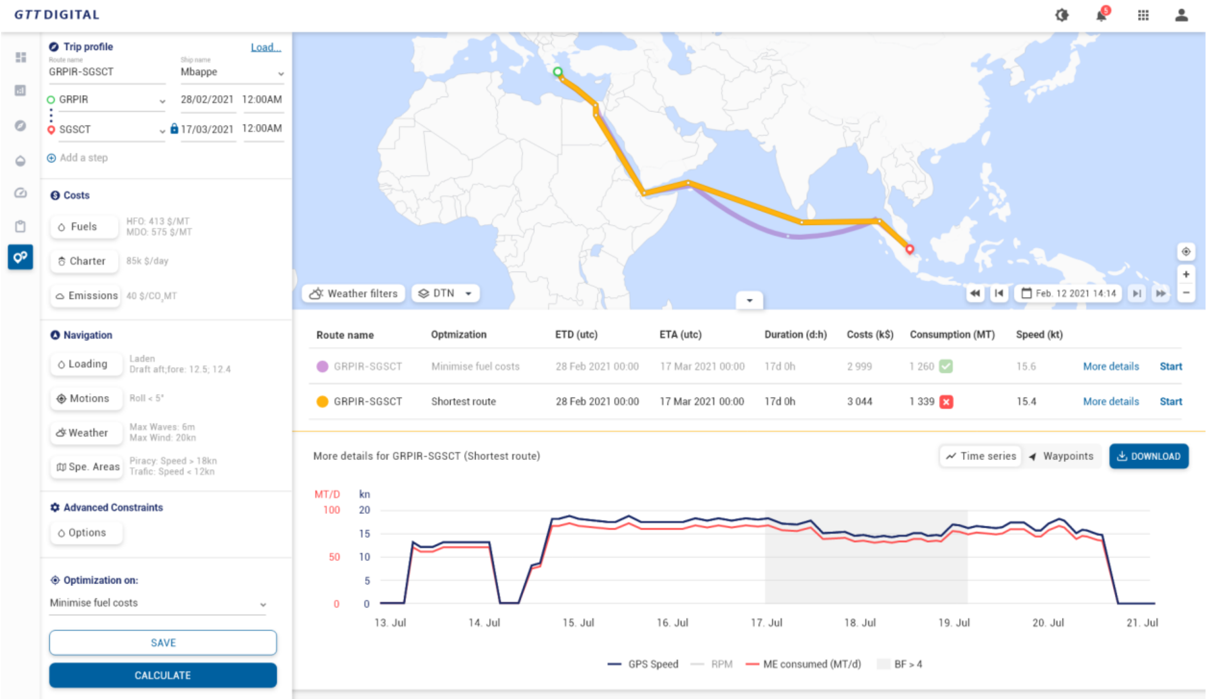


Fig.20: Example of a voyage-based route optimization integrated in the performance system

The pilot tests show good results although expected average savings are regarded limited with 2-3% on the fuel compared with an optimal use of the external weather routing provider. However, it was discovered that not all longer voyages automatically were connected to external weather routing and just by doing so the benefit is somewhat bigger than 2-3%.

3.6. Current efforts and way ahead – Commercial OnePager

The available performance data of more than 100 vessel years is used as base for a so-called Commercial OnePager that will be forwarded to our customers after each voyage – spot as well as charter. The idea behind the OnePager is to present the data available such EEOI, CII, CO_2 emitted, fuel consumed with many more, Fig.21.

This is seldomly requested by our customers representatives, but we want to promote the transparency of our performance when transporting their cargo. The OnePager will be automatically forwarded to our operators, commercials and customers.

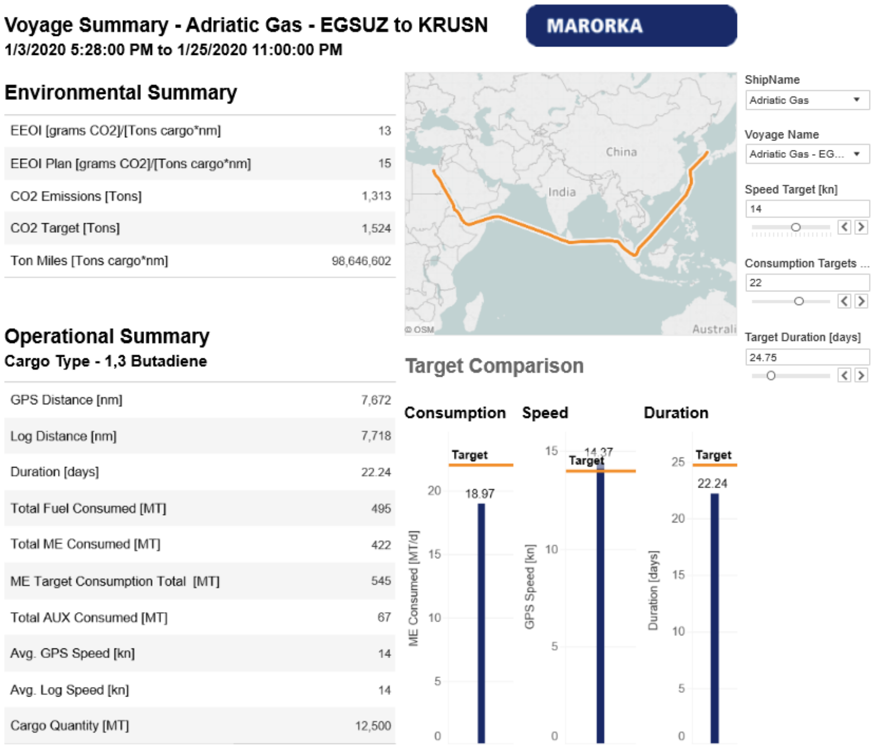


Fig.21: Commercial OnePager

3.7. Current efforts and way ahead – CII, EEOI & EU ETS

Society strives towards a more data driven shipping sector which has resulted in the development of EEXI and CII globally and EU ETS regionally. While EEXI is limitation of power for majority of the fleet instead of a specific speed limitation CII is the first step towards a more data driven quantification of the fleet efficiency later turning into emitted GHG by other instruments yet to be finalized (well-to-wake).

There is no doubt that pure noon reporting as we have seen in the past will not be sufficient and acceptable for society. We will need accurate autolog data to demonstrate as an industry sector full transparency of GHG emitted; where, when and how much – and pay the cost per emitted unit firstly regionally later globally. A fund of shipping money is needed building expertise up globally to ensure available, efficient and low-cost global transport.

As said earlier we have not yet found the best measure for efficiency: CII has only two variables CO_2 emitted and distance but no relation to cargo carried. This means that the simple question for a consumer in a warehouse asking: how much CO_2 emitted has this piece of goods caused until now? cannot be answered for the shipping transport leg. This is not sustainable and has to be changed. Therefore, we have been testing other measures with a link between energy efficiency and commercial figures and are currently using vessel specific EEOI & monthly rates as a measure, Fig.15. However not perfect but more relevant to us than CII although we of course follow and report the development of CII – both vessel by vessel and weighted fleet in accordance with Poseidon's Principle.

Based on autolog data two CII supporting tools have been prepared namely an CII overview tool and a CII prognosis tool. The CII overview tool is for overviewing the development of CII over the year, Fig.22, where the negative impact from idle and low activity early in the year can be seen. Especially, low activity early in the calendar year has a negative effect on the development of CII moving from A to D during a period of 40 days idling although it will gradually improve during the year. However, we have seen charter contracts with very low activity during the year as the vessel has been engaged partly for storage.

Fig.22: CII overview tool – clear negative impact from idling

Furthermore, a fleet CII overview tool showing the development in CII in the years to come based on the current performance and operational profile is available and used for a more strategical approach, Fig.23.

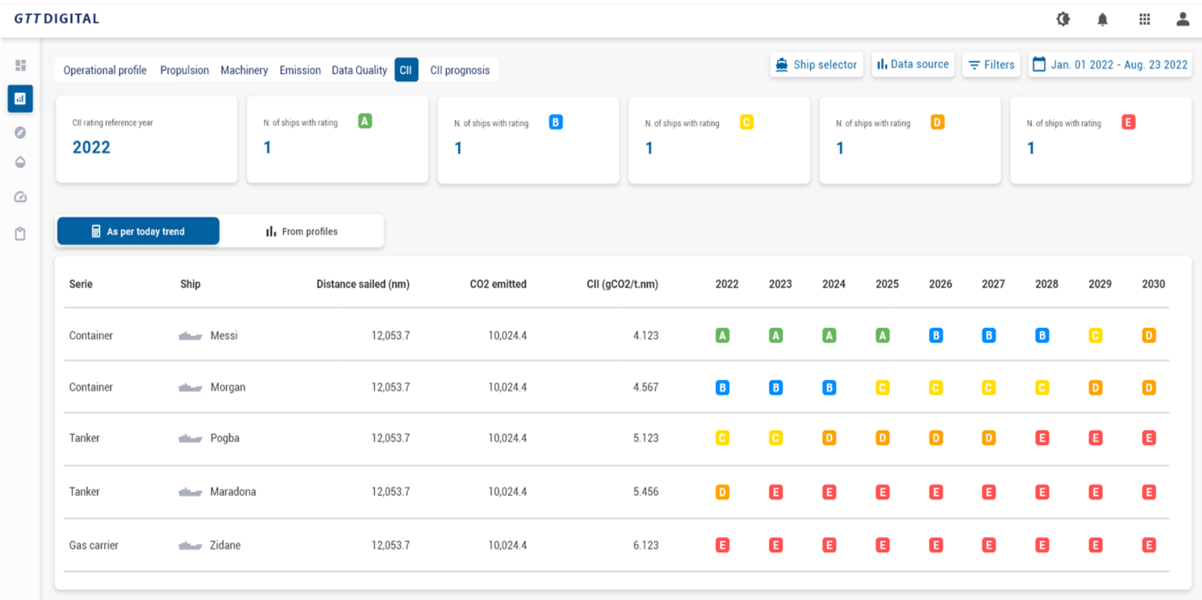
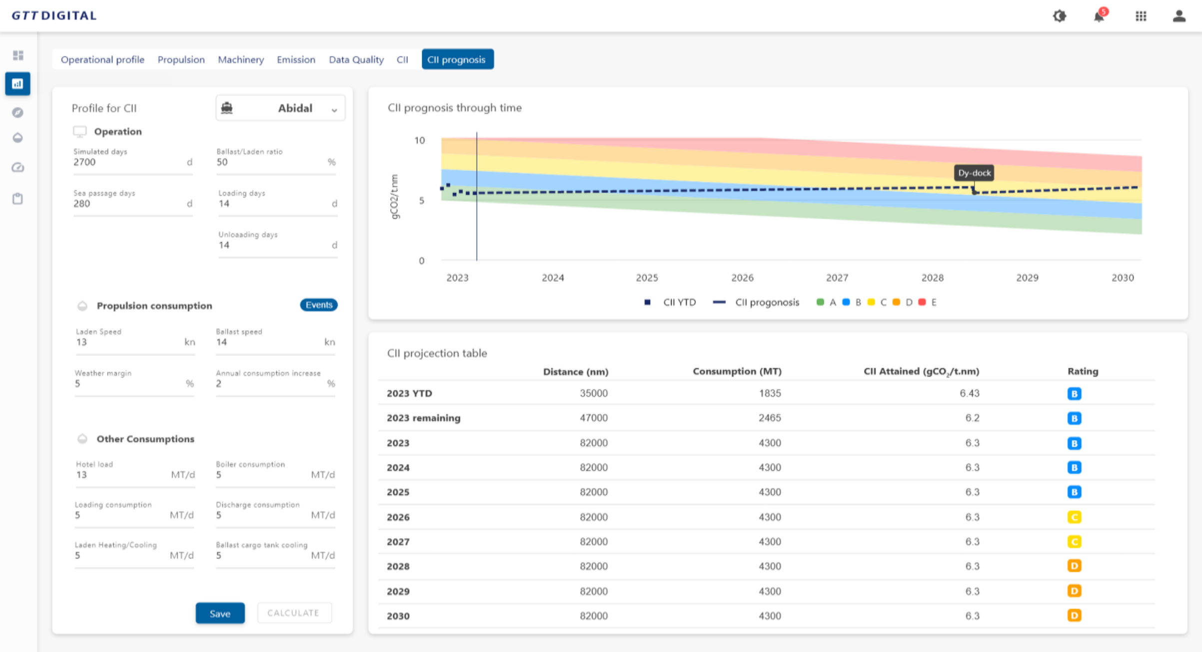


Fig.23: Fleet CII overview tool based on current performance and operational profile

One thing is how the CII is currently developing, and another thing is what will happen if we charter a vessel out for a longer period and the charter speed and consumption agreement results in an A rated vessel are delivered back as D rated. There will be cost associated with bringing the vessel back from D to A as the only variables are consumption and distance meaning that the vessel must sail long distances at assumingly lower speed and consumption losing valuable time.

Therefore, a CII prognosis tool, Fig.24, was developed giving the commercials the possibility to simulate the consequences on CII from planned contract speed and consumption as well as activity.



	Distance (nm)	Consumption (MT)	CII Attained ($gCO_2/t.nm$)	Rating
2023 YTD	35000	1835	6.43	B
2023 remaining	47000	2465	6.2	B
2023	82000	4300	6.3	B
2024	82000	4300	6.3	B
2025	82000	4300	6.3	B
2026	82000	4300	6.3	C
2027	82000	4300	6.3	C
2028	82000	4300	6.3	D
2029	82000	4300	6.3	D
2030	82000	4300	6.3	D

Fig.24: CII prognosis tool simulating the development of CII under a charter party.

This has been a resourceful instrument and useful to discuss the compensation with Charter for redelivery of vessel at end charter with a lower rated CII than received. The CII prognosis tool includes the positive effect from dry docking, hull- and propeller cleaning and retrofitting which cost can be discussed with the Charter.

The energy used for cargo handling (mostly from cargo cooling) can be deducted from CII at a certain rate for gas carriers. This needs to be quantified, which we are currently working on using the many consumption and power data we have from our auxiliary engines and oil-fired boiler. We will present our proposal to the Danish Flag later this Fall.

$$\frac{\sum_j\left(FC_j \cdot C_{Fj}\right) - \left[\sum_j\left(FC_{voyage,j} \cdot C_{Fj}\right)\right] - \left([0.75] - [0.03y_i]\right) \cdot \left[\sum_j\left(FC_{electrical,j} + FC_{boiler,j} + FC_{BOG,j}\right) \cdot C_{Fj}\right]}{f_i \cdot f_m \cdot [f_c] \cdot Capacity \cdot \left(D_t - [D_x]\right)}$$

Fig.24: Deduction in CII for energy used on cargo handling

4. Current efforts and way ahead – Summary

There is no doubt that more accurate performance data are needed in future, and we believe continuing with noon reports will not be sufficient for the level of transparency we want to achieve. The data collected will be used as base for many things apart from efficiency improvement such as setting long term GHG goals, fleet value review and renewal, Scope 1 input, transparency with more.

Navigator Gas is in the process of installing full autolog on the whole fleet, currently having 30+ vessels ready. The better and more accurate performance overview it gives us has already now revealed savings at a magnitude we are quite satisfied with. We believe based on experience that we will be able to cut 15% of the consumption (conservative set) reducing our CO_2 emission by more than 100,000 tons per annum. The total investment will be about USD 2-2.5 mill.

Acknowledgement

I would like to thank my colleagues' patience and understanding as well as GTT/Marorka and JAR Marine for splendid cooperation over the years and are looking forward to some productive years ahead; it has been a pleasure.

Navigating Energy Efficiency Dilemmas in the CII Era

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Abstract

There is a need for a structured approach in evaluating energy efficiency measures and their effects on ships holistically. A key question from ship owners and operators right now is: "How can we make a more educated decision in choosing the right measures?" This is a ship-specific question which requires a ship-specific investigation. With that in mind, Hempel has developed a framework for evaluating different pathways for enhancing energy efficiency before any investment is made on an individual ship. The framework is based on four pillars: operational, regulatory, technoeconomic and environmental. By deploying the framework on a bulk carrier case, we model the effects of widely used biofouling management approaches, bringing new insights to support decision-making on energy efficiency investments. The findings demonstrate that a biofouling management approach that involves the adoption of silicone-based coating, which by design requires no in-water hull cleaning, provides the best investment option across all examined pillars.

1. Introduction

The maritime industries play a critical role in addressing society's needs for global trade and transportation. Shipping goods across the world's oceans and seas represents the most economic means of trade today. Nevertheless, the shipping sector is a significant contributor of Global Greenhouse Gas (GHG) emissions, amounting to roughly 3% of the total GHG globally, *IMO (2021a)*. As the global demand for trade is expected to grow considerably, *Stopford (2022)*, the maritime industries need to expand and develop the existing fleet of vessels. But with the supply of alternative fuels being low during the 2020s, the demand for more trade capacity will be satisfied by vessels that use diesel-powered engines which are expected to dominate the fleet mix until zero-carbon vessels become available. It is estimated that approximately half of all shipping related GHG emissions between 2020 and 2050 will come from diesel-powered vessels (ibid).

A key challenge for the shipping industry is thus related to ensuring short-term reduction of GHG emissions from the existing fleet through operational measures and technical upgrades, using the energy efficiency technologies and measures that are currently available. These may include, among others, installation of energy saving devices, the use of biofuels in the fuel mix, or increasing the frequency of dry dockings to refresh the coating system and improve energy ratings. Silicone-based and other advanced antifouling coating systems are one of the most mature technology upgrades that can provide immediate improvement to ship energy efficiency, *ABS (2021)* and *IMO (2023a)*. The choice of antifouling coatings is part of the vessel biofouling management plan which also involves implementing relevant monitoring and maintenance activities, including the regiment of in-water hull cleaning and propeller polishing. Biofouling management can enhance vessel hydrodynamics and energy efficiency by ensuring a clean hull throughout the docking cycle, and by extension significantly reduce vessel GHG emissions, *IMO (2022,2023b)*.

With multiple approaches suggested by industry and academia for the most optimal energy efficiency measures and investment, ship owners and operators are facing a key question: "How can we make a more educated decision in choosing the right measures?" This is a ship-specific question and thus requires a framework to evaluate ship-specific parameters. To this end, Hempel has developed a comprehensive framework to support the maritime industries with navigating energy efficiency dilemmas. The framework provides a holistic analysis of different pathways to increase energy efficiency ratings and reduce GHG emissions. With this paper we demonstrate the utilization of the

Hempel framework to evaluate alternative energy efficiency measures with focus on biofouling management.

A recent report from the IMO GloFouling Project, *GEF-UNDP-IMO (2022)*, reiterates that if left unmanaged, biofouling can significantly increase frictional resistance and GHG emissions. The same report outlines a series of biofouling prevention and management measures to support in-service vessels and depicts the impact of alternative scenarios on fuel consumption and GHG emissions. Specifically, the report focuses on the in-service measures such as in-water hull cleaning, propeller polishing, and other operations that take place while the vessel is in the water. Although it emphasizes that “anti-fouling coatings are the first and foremost tool […] to prevent biofouling” (p.13), it does not consider the choice and performance of alternative antifouling coating systems.

The aim of this paper is to enhance the analysis presented by *GEF-UNDP-IMO (2022)* by incorporating alternative coating technologies and providing a more comprehensive framework that extends beyond fuel consumption and GHG emissions. Specifically, the paper examines the performance of the same vessel as the one used in initial report, but adds an additional scenario for silicone-based low friction coating, while also conducting a more holistic analysis that considers the impact of alternative biofouling management approaches on the total fuel consumption, variations in Carbon Intensity Indicator (CII) rating, EU ETS carbon costs, as well as Total Cost of Ownership (TCO) and payback period over a docking cycle of 5 years.

2. The Hempel framework for evaluating ship energy efficiency measures

Hempel has developed a decision framework to support the maritime industry in evaluating ship energy efficiency measures, which also include biofouling management. The framework assesses these measures across four essential pillars: (1) vessel trade and operational profile, (2) regulatory requirements and compliance, (3) TCO and payback period, (4) environmental considerations and sustainability. The framework enables the analysis of these options to yield vessel-specific results, offering valuable insights tailored to each individual ship. Fig.1 illustrates the four pillars of the framework.

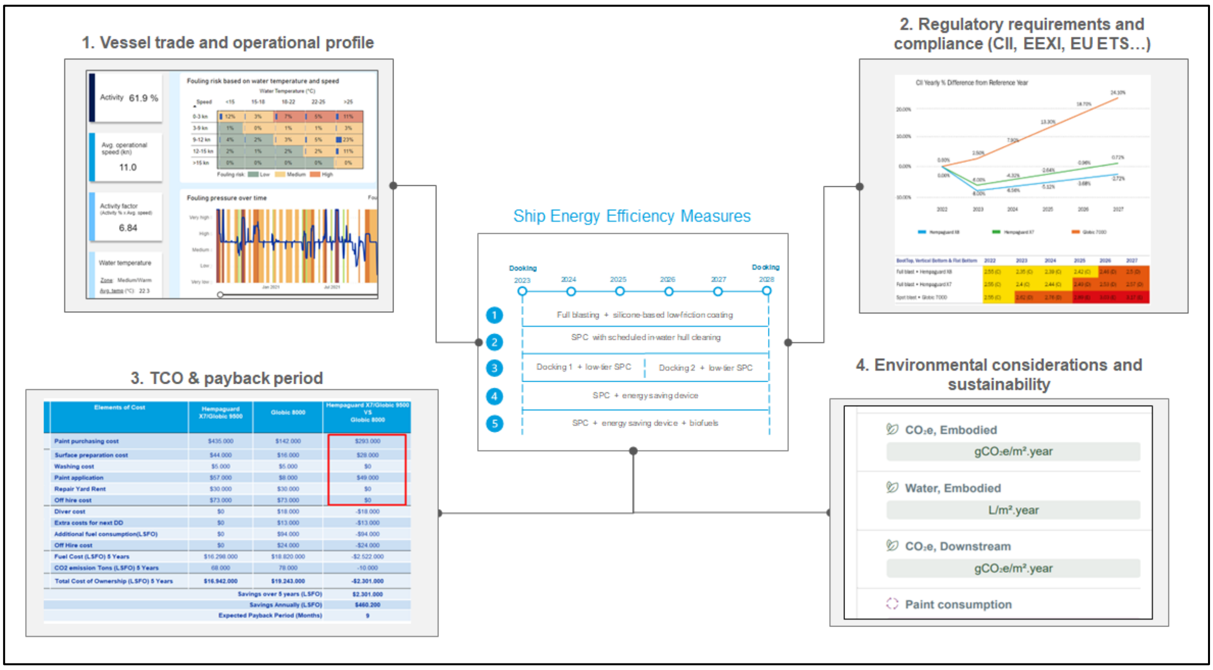

Fig.1: The Hempel Framework for ship-specific assessment

(1) Vessel trade and operational profile: This section of framework focuses on testing each measure on the specific operational profile of the vessel (historical or expected) to identify the following:

- Biofouling risk, considering location, idle periods (AIS data) in aggressive waters (oceanographic data), speeds and requirement for operational flexibility, assessment of current hull condition and outlook for deterioration based on expected performance of coating in use, historical underwater data from past diving reports and hull interventions.
- Risk of increasing CII due to operation including idle periods, short voyages, and prolonged port stays.
- Alignment of coating specification with the vessel-specific trade pattern, including product per hull area, number of coats, dry film thickness.
- Risk of mechanical damages due to canal transits, ice trading, ship-to-ship operations, berthing conditions and other relevant parameters.

(2) Regulatory requirements and compliance: This section of the framework considers global policy frameworks set forth by organizations like the International Maritime Organization (IMO) and the European Union (EU). It simulates the potential impact of each energy efficiency measure considered by the owner and/or the operator on various regulatory aspects, including the Carbon Intensity Indicator (CII) rating, Vref for the Energy Efficiency Existing Ship Index (EEXI), and EU Emissions Trading System (ETS) compliance. The framework allows for adjustments to consider future regulatory developments. The upgrades under consideration may involve an antifouling coating system or a combination of multiple energy efficiency upgrades.

(3) Total Cost of Ownership (TCO) and payback period: In this section of the framework, the TCO of each energy efficiency measure is quantified including all costs associated with their installation and in-service operation and maintenance. The analysis provides valuable insights into the expected payback period from each measure considered by the owner and/or the operator of the vessel. It also considers factors such as fuel cost responsibility (e.g., owner vs. operator) to provide a comprehensive assessment of the financial implications of adopting these technologies.

(4) Environmental considerations and sustainability: In this section, the framework considers the sustainability profile of retrofit systems, and factors such as expected durability, required maintenance, and installation. For coating systems, it is important to consider the impact during installation (e.g., volatile organic compounds) and in-service impact (e.g., biocidal content and microplastics). Hempel's product sustainability scorecard provides insights into the products' impact based on nine different metrics that focus on environment, circularity, and chemical safety.

For this paper, we primarily focus on the sections of the framework that align with the aim of this study. As the vessel used in this initial study, *GEF-UNDP-IMO (2022*) has pre-defined trading parameters in the Mediterranean Sea (pillar 1), our main emphasis will be on extending pillar 2 (regulatory aspects concerning the Carbon Intensity Indicator - CII rating and EU ETS carbon costs) and pillar 3 (TCO and payback period). To ensure comparability with the initial study we do not consider the 4th pillar.

Two fundamental models within the Hempel framework, which are relevant to discuss while exploring pillars 2 and 3, are the fuel consumption model and the cost model. Adapted from *Demirel et al. (2017)*, these models are tailored to analyze investments in new coating systems and simulate variations in total fuel consumption, CII, EU ETS carbon costs, TCO and payback period, across biofouling management approaches. To ensure comparability with the initial study, *GEF-UNDP-IMO (2022)*, certain limitations have been incorporated into the models.

2.1 Fuel consumption model

The fuel consumption of a ship is significantly influenced by the condition of its hull surface, as increased hull roughness leads to higher frictional resistance. Each ship is designed for specific operating conditions, and there is a predetermined power requirement to achieve a particular speed. However, during the vessel's service life, the required power gradually increases due to various factors, including biofouling accumulation, mechanical degradation of the coating, and reduced efficiency of the ship's mechanical systems. For the sake of simplicity and to stay within the scope of this paper, we will categorize all non-coating and non-biofouling-related power increases, as well as any unrecoverable increases, as 'aging.' Therefore, the required power to achieve a certain speed at any given time can be simplified as follows:

$$P_{B\_t} = P_{B\_initial} + \Delta P_{B\_biofouling} + \Delta P_{B\_mechanical} + \Delta P_{B\_aging}$$

P_{B_t} is the required brake power at any time, $P_{B\_initial}$ is the design brake power, $\Delta P_{B\_biofouling}$ the increase in brake power due to biofouling, $\Delta P_{B\_mechanical}$ the increase in brake power due to mechanical deterioration of the coating, and ΔP_{B_aging} the increase in brake power due to the aging of the ship. In this case, $\Delta P_{B\_fouling} + \Delta P_{B\_mechanical}$ are directly related to the selected coating system and the biofouling management measures. Once these values are known or predicted, the corresponding increase in fuel consumption over time can be determined. It is assumed that the increase in fuel consumption is directly proportional to the increase in power, as illustrated in the equation below:

$$\frac{P_{B\_t}}{P_{B\_initial}} = \frac{Fuel_t}{Fuel_{initial}}$$

$Fuel_{initial}$ is the fuel consumption per mile at the design stage and $Fuel_t$ is the fuel consumption per mile at any time. Given that the initial fuel consumption of a ship ($Fuel_{initial}$) is known, the fuel consumption at any time can be obtained using the above equation.

Considering the information provided above, every ship has a higher required power and higher fuel consumption at the end of the docking cycle than at the beginning of a docking cycle. Our proposed model simulates scenarios starting from the end of one docking cycle until the end of the subsequent docking cycle, just before the ship enters the dry dock again.

The choice of coating system and other energy efficiency technologies has a direct impact on the required power and, consequently, fuel consumption immediately after the dry dock, exerting its influence throughout the entire docking cycle. Moreover, the choice of coating system also have a significant impact on the accumulation of biofouling and the sensitivity towards mechanical deterioration of the coating, which in turn affects fuel consumption over time.

The impact of such choices can be observed on the required power and, hence, fuel consumption (and CII), by considering four factors:

(1) Standard improvement from dry dock by washing and cleaning the hull, regardless of coating application. This procedure is assumed to remove any biofouling deposits from the hull.
(2) Improvement from surface preparation and coating application. Full blasting and coating application are assumed to remove the effects of mechanical deterioration of the coating over time. In the case of spot repairs, a partial recovery of $\Delta P_{B\_mechanical}$ is assumed, resulting in required power 2.5% higher than that of the full-blasting scenario. This assumption is based on a high-frequency confidential dataset.
(3) Immediate power gain after the application of silicone-based coatings due to smoothness compared to SPCs and/or the application of other energy efficiency technologies. It is important to note that this power gain refers to a further reduction in the initial required power, $P_{B\_initial}$. Silicone-based topcoats are reported to consistently decrease the frictional resistance compared to SPC type paints, as shown by *Candries and Atlar (2005), Schultz (2004), Demirel (2015).*
(4) Increase in power over time due to mechanical deterioration of the coating, biofouling accumulation and aging. The speed loss of a given coating system according to ISO 19030 is translated into the yearly added power. Differences in speed loss between coating systems result in different rates of deterioration, directly impacting the fuel consumption, and CII, assuming operation is equal.

The first three factors mentioned above directly affect the required power and, consequently, the fuel consumption of ships immediately after dry-docking when their hulls are clean and biofouling-free. On the other hand, the fourth factor influences the required power and fuel consumption over time, as it represents the variation in required power after the dry-dock as a function of time due to hull degradation worsening over time.

2.2 Cost model

Total Cost of Ownership (TCO) refers to the overall costs related to the selected coating system and/or other energy efficiency measures incurred by a shipowner or operator throughout a docking cycle. TCO can be defined by the equation below:

$$TCO = Cost_{dry-dock} + Cost_{voyage}$$

where TCO is the total cost of ownership over the docking cycle, $Cost_{dry-dock}$ is the cost of all activities when the ships are in dry dock, and $Cost_{voyage}$ is the cost of all activities when the ships are in operation.

$$\begin{gathered} Cost_{dry-dock} = Washing\ and\ cleaning\ cost + surface\ preparation\ cost \\ + purchase\ and\ application\ cost\ of\ coating\ and\ other\ energy\ efficiency\ measures \\ + repair\ yard\ rent\ cost + off - hire\ cost \end{gathered}$$

$$Cost_{voyage} = Fuel\ cost + Operational\ cost\ associated\ with\ the\ energy\ efficiency\ measures$$

The term '$Operational\ cost\ associated\ with\ the\ energy\ efficiency\ measures$' encompasses a range of expenses, including but not limited to inspection and cleaning costs related to biofouling management approaches. It is important to note that the fuel cost can be directly influenced by several factors, including the ship's design and operations, the in-service performance of the selected coating system combined with energy efficiency measures, and the aging effect over time. These factors play a significant role in determining the overall fuel consumption and associated costs during the ship's operational life.

3. Case study

This paper takes a point of departure from the case study entailed in *GEF-UNDP-IMO (2022)*. The focus of *GEF-UNDP-IMO (2022)* was on a bulk carrier coated with a Self-Polishing Coating (SPC) system, as also studied by *Uzun et al. (2019). GEF-UNDP-IMO (2022)* explored the potential for greenhouse gas (GHG) reduction through various biofouling management scenarios, namely: 1) the use of only SPC, 2) SPC with responsive cleaning, and 3) SPC with regular cleaning. The study predicted the impact of these biofouling management scenarios on the ship's required power, fuel consumption, fuel costs, and total CO_2 emissions over a 5-year docking cycle. However, it is essential to note that *GEF-UNDP-IMO (2022)* solely considered SPC-type coatings in all three scenarios and did not account for any other costs associated with the biofouling management activities.

Building upon the analysis presented in *GEF-UNDP-IMO (2022)*, the current study goes a step further by integrating a silicone-based low friction coating into the investigation. Through a more comprehensive approach, it evaluates the influence of the selected biofouling management strategies on the total fuel consumption, CII rating variations, EU ETS carbon costs, and Total Cost of Ownership (TCO) and payback period throughout a 5-year docking cycle. As a result, this study seeks to offer a more encompassing overview that can better inform industry stakeholders and policymakers alike.

It is essential to note that this study provides a limited subset of the comprehensive results obtained through the Hempel framework to maintain comparability with the original report. The focus is on specific aspects of interest. Table I displays the principal particulars and selected biofouling management scenarios for the target vessel.

Table I: Principal particulars and selected biofouling management scenarios of the target vessel (adapted from *GEF-UNDP-IMO (2022)*)

Vessel type	Bulk carrier
Deadweight	40,000 t
Length	179 m
Breadth	28 m
Design draft	10.6 m
Wetted surface area	7,350 m^2
Speed	14 knots
Fuel consumption (clean - SPC)	20.4 t/day
Operating region	Mediterranean region
Operation period	5 years
Biofouling management scenarios*	Scenario 1: SPC - no in-water cleaning Scenario 2: SPC + responsive cleaning Scenario 3: SPC + regular cleaning Scenario 4: Silicone-based low friction coating - no in-water hull cleaning

*The terminology referring to cleaning regimes is slightly different from the *GEF-UNDP-IMO (2022)*. This is because the 2023 IMO Biofouling Guidelines, *IMO (2023b)* differentiate proactive and reactive cleaning based on the size of biofouling on the hull, not based on frequency or number of cleaning interventions. Specifically, according to *IMO (2023b)*, proactive cleaning only refers to cleaning of microfouling while reactive cleaning refers to macrofouling cleaning. Scenarios 2 and 3 represent alternative cleaning frequencies with no reference to the type or size of biofouling growth on the hull. As such, we opted not to use the term "proactive cleaning" to prevent any confusion with the term used in the recently updated *IMO (2023b)*.

3.1. Assumptions

Scenarios 1, 2, and 3 are directly taken from *GEF-UNDP-IMO (2022)*, and the same assumptions were utilized. Scenario 4 is based on a silicone-based low friction coating available in the market. The analysis considers the ship under study entering dry-dock and the adoption of the listed biofouling management scenarios.

3.1.1. Fuel consumption

Table II: The analyzed biofouling management scenarios and assumptions used

Biofouling management scenario number	Hull coating	Hull related measures	Propeller related measures	Assumptions used
Scenario 1	SPC AF coating	No	No	Assumption 1** Assumption 2** Assumption 4** Assumption 8
Scenario 2	SPC AF coating	Hull cleaning after 3 & 4 years	Propeller cleaning after 3 & 4 years	Assumption 1** Assumption 2** Assumption 3** Assumption 4** Assumption 5** Assumption 8
Scenario 3	SPC AF coating	Hull cleaning after 1 ½, 2, 2 ½, 3, 3 ½, 4, 4 ½ years	Propeller cleaning after 1 ½, 2, 2 ½, 3, 3 ½, 4, 4 ½ years	Assumption 1** Assumption 2** Assumption 3** Assumption 4** Assumption 6** Assumption 8
Scenario 4	Silicone-based low friction coating	No	Propeller polishing, twice a year	Assumption 9 Assumption 10

**See *GEF-UNDP-IMO (2022)* for the description of the assumptions.

Table II shows the assumptions used for the analyzed biofouling management scenarios, and Table III shows the details of the assumptions used for the present study.

Table III: The details of the assumptions used for the present study

Assumptions	Description
Assumption 8	1. The bulk carrier enters drydock at the end of 2023 and leaves the dry-dock on 1st January 2024. 2. The bulk carrier was assumed to be coated with an SPC in the previous docking cycle, and it entered the dry-dock with biofouling growth and mechanical degradation of the coating. The impact from ageing is ignored. 3. Spot blasting (40%) was conducted before the application of the SPC in the current dry-dock. 4. The increase in power due to the aging of the ship, ΔP_{B_aging} is disregarded for both the current and previous docking cycle.
Assumption 9	1. The bulk carrier enters drydock at the end of 2023 and leaves the dry-dock on 1st January 2024. 2. The bulk carrier was assumed to be coated with an SPC in the previous docking cycle, and it entered the dry-dock with biofouling growth and mechanical degradation of the coating. The impact from ageing is ignored. 3. Full blasting was conducted before the application of the silicone-based low friction coating in the current dry-dock. 4. Immediate power gain after the application of silicone-based low friction coating compared to SPC is assumed to be 6% based on the Hempaguard technology of Hempel (*Bertelsen and Meseguer Yebra, n.d.*). 5. Considering the points above, the decrease in the ship's required power (at the same speed) due to the silicone upgrade during dry-dock is estimated to be 8.5% (2.5% + 6%) compared to the required power of the ship that underwent spot blasting and was coated with SPC, corresponding to scenarios 1, 2, and 3. 6. The increase in power due to the aging of the ship, ΔP_{B_aging} is disregarded for the previous docking cycle.
Assumption 10	The increase in power over time, attributed to mechanical deterioration of the coating, fouling accumulation, and aging is assumed to result in a 1.4% speed loss over a 5-year period. This represents the guaranteed maximum average speed loss of a vessel with the Hempaguard X7 coating system, as per ISO 19030.

3.1.2. Cost

Table IV shows the assumptions used for cost calculations.

Table IV: Elements of costs and the assumptions used

	Elements of cost	Definition
Paint	**Paint purchasing cost**	Cost of paint project purchased from paint supplier
Repair yard	**Surface preparation cost**	Cost of sweeping/blasting before washing
	Washing cost	Cost of high-pressure fresh water washing before applying the paint
	Paint application cost	Cost of applying the paint
	Repair yard rent	Drydock rent * No. of days for [washing + blasting + paint application + undocking]
	Off hire cost	Off-hire is the time the ship is prevented from being hired due to repairs. No. of days in dock * Average charter rate
Cleanings	**Diver cost**	Number of cleanings in 5-yr interval * typical diver cost
	Off-hire cost	Off-hire is the time the ship is prevented from being hired due to cleanings. No. of days needed for cleanings * Average charter rate

3.1.3. In-water hull cleaning

The authors of this study acknowledge certain limitations, especially in relation to the effects of in-water hull cleaning. Specially, this study does not consider the impact of frequent in-water hull cleaning interventions on the coating systems and the water column. The dataset from *GEF-UNDP-IMO (2022)* used in the case study has the same limitations. To ensure a fair and consistent comparison, the current study adopts the same assumptions, thereby inheriting the same limitations as the *GEF-UNDP-IMO (2022)*. For illustration the below constitute critical points which are not considered in this study:

- In-water hull cleaning can reduce the active lifetime of a coating system. This is especially true for Self-Polishing Coatings (SPCs), which may not maintain effectiveness for the full 5-year duration unless additional DFT is applied initially. The in-water hull cleaning process, while it removes biofouling from the hull, will reduce the coating's effective lifetime. This may lead operators to further increase the frequency (and costs) of in-water hull cleaning – especially in year 4 and 5. Alternatively, a more resource-intensive coating system with higher DFT (and cost) will be required to withstand frequent hull cleaning interventions and ensure hull protection and performance.
- In-water hull cleaning services are not always available when needed. This means that a vessel may need to operate with added biofouling growth on the hull and hence a fuel penalty until it arrives at a location where cleaning services are available and permitted. In our modelling, like the initial study, there is an assumption that in-water hull cleaning is always available when needed at specific time intervals.
- The significance of cautious cleaning activities cannot be overstated. Incorrect in-water cleaning practices may damage coating systems, causing accelerated biofouling accumulation, increased drag, and higher fuel consumption. Incorrect hull cleaning practices may remove biofouling but also damage the coating, resulting is faster re-fouling rates. While *GEF-UNDP-IMO (2022)* acknowledged the possibility of coating damage due to cleaning activities, it did not consider the potential impact on biofouling growth rates from damaged surfaces. To ensure a fair comparison, the present study maintains the same assumption and does not consider the variation in regrowth rates following frequent in-water hull cleaning activities.
- An increased frequency of in-water hull cleaning operations may require additional time and costs associated with pre- and post-cleaning hull inspections to determine the sections requiring cleaning and to document the cleaning effect afterwards. These costs are not considered in *GEF-UNDP-IMO (2022)* nor in this study.
- Potential damages to the coating system from frequent in-water cleaning operations may lead to extra costs and activities during subsequent dry-docks in terms of surface preparation. These costs are not considered in *GEF-UNDP-IMO (2022)* nor in this study.
- *GEF-UNDP-IMO (2022)* assumed that biofouling growth is uniformly distributed on the hull wet surface and that any in-water hull cleaning intervention would result to the entire hull and propeller being fully clean. However, biofouling growth tends to be concentrated on certain hull sections and it is not practically possible for in-water hull cleaning operations to achieve a completely clean hull as measured by the entire wet-surface area. Contrary, there are sections which are not cleaned due to operational reasons. Priority is usually given to the areas that can have a strong effect to fuel efficiency (i.e., vertical sides) or to the areas relevant for biosecurity compliance (i.e., niche areas). Also, it is common for vessels to have very limited time alongside at port terminals or anchorages, which results in partial cleaning each time and multiple cleaning interventions to achieve a "clean hull". The present study retains the same assumptions with the *GEF-UNDP-IMO (2022)* to align with the original study's methodology and ensure comparability.
- Although the current study focuses primarily on fuel consumption and subsequent CO_2 emissions, it is important to recognize that in-water cleaning activities may increases the risk of chemical and biological contamination because of waste substances released into the water column. Although this is beyond the scope of this paper, it remains a critical avenue for further research.

3.2. Results

3.2.1. Required power change

Fig.2 shows the increase in the required power of the bulk carrier to maintain the 14 kn design speed. The required engine power increases for the first three scenarios are directly taken from *GEF-UNDP-IMO (2022)*. The required engine power for scenario 4, has been calculated based on the information provided in Section 2.1 and the assumptions provided in Section 3.1. The negative value at Year 0 is attributed to the immediate power gain observed after the full blasting process and application of a silicone-based coating, which results in a smoother surface compared to a conventional SPC.

The different scenarios analyzed in the study show varying effects on the required power for ship operation. The ‘SPC - no in-water cleaning’ scenario (scenario 1) exhibits the most severe increase in required power, reaching up to 45%. Conversely, the ‘SPC + responsive cleaning’ (scenario 2) and ‘SPC + regular cleaning’ (scenario 3) scenarios demonstrate immediate drops in power requirements upon the application of cleaning measures. At the end of the docking cycle (Year 5), the power increase values for ‘SPC + responsive cleaning’ and ‘SPC + regular cleaning’ scenarios are 19% and 6%, respectively, *GEF-UNDP-IMO (2022)*. Notably, the ‘Silicone-based low friction coating - no in-water hull cleaning’ (scenario 4) scenario outperforms others, thanks to the combined benefits of an initial power gain after dry-docking and a slow deterioration over time. The power starts at -8.5% and linearly increases to -0.1% compared to a clean SPC coated surface (if always clean). However, focusing solely on power increase values may be misleading when comparing different options, as the primary difference lies in the total fuel consumed during the docking cycle. Therefore, a comprehensive assessment considering overall fuel consumption is crucial for making informed decisions.

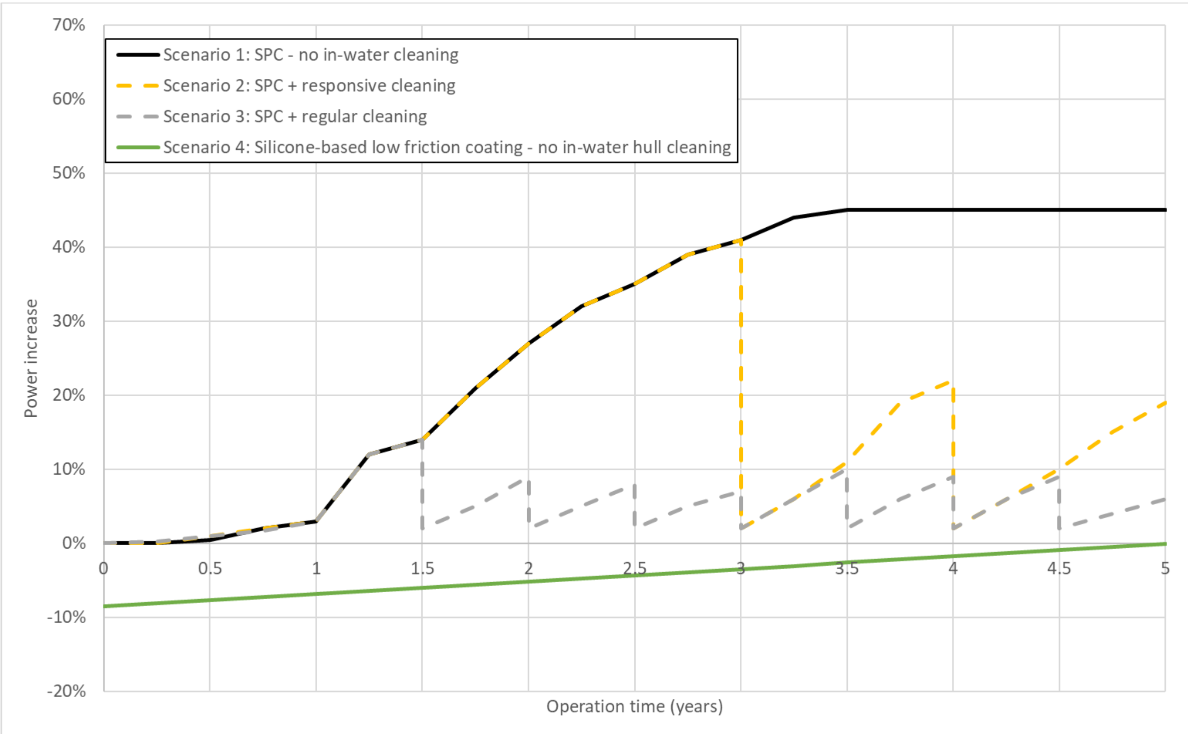

Fig.2: Required power increase of a bulk carrier with different biofouling management strategies over the 5-year operation, adapted from *GEF-UNDP-IMO (2022)*

3.2.2. Cumulative fuel consumption

Fig.3 presents a comparison of the cumulative fuel consumption of the bulk carrier under different biofouling management scenarios. The cumulative fuel consumption values for the first three scenarios are directly taken from *GEF-UNDP-IMO (2022)*. The cumulative fuel consumption for scenario 4, namely silicone-based low friction coating with no in-water hull cleaning, has been calculated based on the information provided in Section 2.1, and the assumptions provided in Section 3.1.

As the operation time extends, the variations in cumulative fuel consumption between the scenarios become more distinct. The results from the original report indicate that scenario 2 (SPC - no in-water cleaning) results in a total fuel consumption exceeding 46,000 tons over the 5-year period. Implementing responsive cleaning (scenario 2), which involves hull and propeller cleaning after 3 and 4 years of operation, reduces the total fuel consumption to below 42,000 tons. Adopting a regular cleaning strategy (scenario 3) further reduces the total fuel consumption to below 38,000 tons, *GEF-UNDP-IMO (2022)*. The results from the present study emphasize the significant potential for fuel savings by choosing a silicone-based low friction coating (scenario 4), as the total fuel consumption can be decreased to below 35,000 tons. These findings underscore the impact biofouling management activities can have in optimizing fuel efficiency for bulk carriers and highlight the substantial fuel-saving benefits of adopting a silicone-based low friction coating.

The total fuel costs for the 5-year operation of the bulk carrier were estimated based on predicted fuel consumption under different scenarios. Table VII illustrates the total fuel cost of the bulk carrier across various biofouling management scenarios, with calculations based on a fuel price of 572.5 USD per metric ton of FO fuel. The findings indicate that the total fuel cost over the 5-year operation can reach ~$26.70 million under scenario 1. However, this cost is reduced to ~$23.85 million and ~$21.80 million under scenario 2 and scenario 3, respectively, *GEF-UNDP-IMO (2022)*. Adopting a silicone-based low friction coating can further decrease the total fuel cost to ~$19.95 million. Table VII provides a comprehensive comparison of the differences in total fuel costs between the different biofouling management strategies.

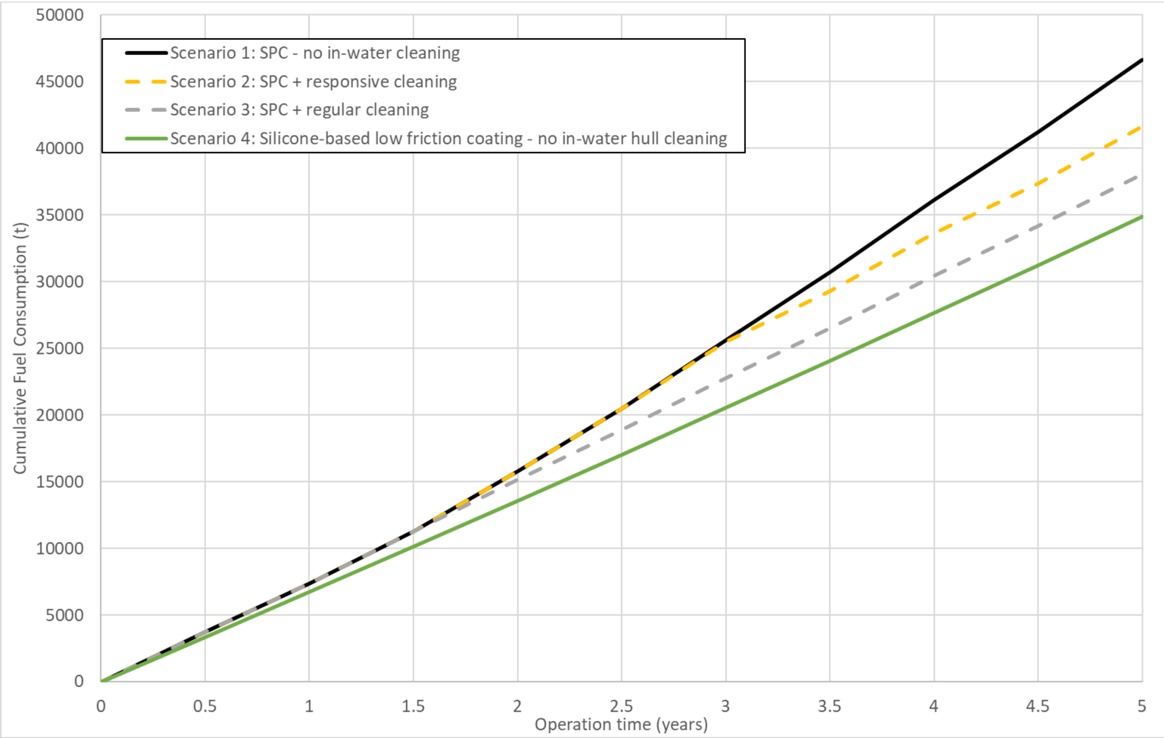

Fig.3: Cumulative fuel consumption of the bulk carrier with different biofouling management strategies over the 5-year operation, adapted from *GEF-UNDP-IMO (2022)*

3.2.3. Carbon Intensity Indicator (CII)

The CII (Carbon Intensity Indicator) is a measure for a ship's energy efficiency and is given in grams of CO_2 emitted per cargo-carrying capacity and nautical mile, *DNV (2023)*.

Since the nautical miles of the ship operated in this cycle and the attained CII of the previous year before the dry-dock are unknown, we relied on a set of assumptions to derive a representative CII value and demonstrate the impact of each scenario on the CII rating. The following assumptions were used:

- The ship enters drydock at the end of 2023 and leaves the dry-dock on 1st January 2024 so that the effect of each scenario would fully impact the CII of 2024 onwards.
- Required annual operational CII, $CII_{required}$, in 2024 is the attained CII of the 'ideal ship'. This 'ideal ship' is assumed to remain unaffected by any biofouling accumulation, coating

degradation, or aging in 2024. In simpler terms, the sum of $\Delta P_{B\_fouling}$, $\Delta P_{B\_mechanical}$, and ΔP_{B_aging} is considered to be zero for the 'ideal ship' in 2024.

- The reduction factors for Phase 3 (2027 – 2030) have not yet been announced. A 3% reduction was assumed for this specific period.

By using the assumptions above, we can directly see the effect of each selection on the CII starting from the 1st year compared to an 'ideal ship' that is operating without any increase in the required power. The details of CII can be seen in *IMO (2021b; 2021c; 2021d; 2021e).*

Using the methods mentioned above, the theoretical CII of the 'ideal ship' is calculated to be 6.056 in 2024. The effect of each option on the CII value was then calculated for each year, Table V.

Table V: The CII values of the ship under different biofouling management scenarios

	2024	2025	2026	2027	2028
Scenario 1	6.12 (C)	7 (E)	8.19 (E)	8.72 (E)	8.76 (E)
Scenario 2	6.12 (C)	7 (E)	8.09 (E)	6.74 (E)	6.69 (E)
Scenario 3	6.12 (C)	6.49 (D)	6.33 (D)	6.38 (D)	6.35 (D)
Scenario 4	5.59 (B)	5.69 (C)	5.8 (C)	5.9 (C)	6 (D)

The CII analysis across the different biofouling management scenarios reveals important insights into the energy efficiency, environmental impact, as well as a critical compliance consideration. According to IMO regulations, a vessel that receives three consecutive "D" ratings or a single "E" rating in a given year is mandated to develop and present a corrective action plan, outlining the strategies to attain a CII index of "C" or higher. This underscores the significance of adhering to the established efficiency standards. Furthermore, as stipulated by the IMO, there is a proactive encouragement for administrations, port authorities, and relevant stakeholders to offer incentives to ships that achieve "A" or "B" ratings, fostering an environment of enhanced energy efficiency and sustainability within the maritime industry.

Scenario 4 (Silicone-based low friction coating - no in-water hull cleaning) consistently demonstrates favorable CII values for each year, starting at 5.59 g of CO_2 emitted per cargo-carrying capacity and nautical mile in 2024 (B rating). It gradually increases to 5.69 (C) in 2025, 5.8 (C) in 2026, 5.9 (C) in 2027, and finally reaches 6 g (D) in 2028. These CII values for scenario 4 show the considerable emission reduction potential that the shipping industry can achieve today with the available silicone coating technologies. On the other hand, scenario 1 (SPC - no in-water cleaning) and scenario 2 (SPC + responsive cleaning) exhibit higher CII values with consecutive E ratings, indicating non-compliance with the regulatory threshold, relatively lower energy efficiency and higher environmental impact over multiple years. Scenario 3 (SPC + regular cleaning) demonstrates consecutive D ratings, which do not comply with the regulatory requirement of avoiding three consecutive D ratings. Ships operating under these scenarios will need to implement additional measures to improve energy efficiency and reduce their CII ratings to align with the regulations set by the IMO. These findings underscore the significance of selecting biofouling management strategies that prioritize energy efficiency and reduce carbon emissions while ensuring compliance with the established energy efficiency standards.

3.2.4. EU ETS carbon cost

The EU ETS is a cap-and-trade system designed to reduce GHG emissions by imposing a cap on emissions for specific economic sectors. The shipping sector has been included in the EU ETS from 2024 onwards. Table VI presents the annual EU ETS carbon costs for each biofouling management scenario.

It is important to highlight that the vessel used in this study already has pre-defined trading region of Mediterranean Sea, *GEF-UNDP-IMO (2022)*. However, the specific intricacies of the trading parameters remain undisclosed. Hence, we relied on a series of assumptions to establish representative

EU ETS carbon costs and to showcase the influence of each scenario on the EU ETS carbon cost. The following assumptions were considered:

- All operations occur within the Mediterranean Sea throughout the 5-year docking cycle.
- 60% of the operations involve travel between EU ports, while the remaining 40% involve journeys between EU and non-EU ports.

In the years 2024, 2025, 2026, 2027, and 2028, the percentages of eligible emissions to consider for EU ETS Carbon costs are 40%, 70%, 100%, 100%, and 100%, respectively. EU ETS carbon price is assumed to be $90. This carbon price represents the cost of emitting one ton of carbon dioxide equivalent (CO2e) into the atmosphere under the European Union Emissions Trading System (EU ETS).

Table VI: Yearly EU ETS carbon costs of the ship under different biofouling management scenarios

Scenarios	2024	2025	2026	2027	2028	Total
Scenario 1	$659,441	$1,321,482	$2,207,104	$2,351,478	$2,361,518	$8,901,022
Scenario 2	$659,441	$1,321,482	$2,182,127	$1,816,054	$1,804,891	$7,783,995
Scenario 3	$659,441	$1,225,397	$1,707,617	$1,719,178	$1,711,584	$7,023,216
Scenario 4	$603,114	$1,074,652	$1,562,649	$1,590,081	$1,617,513	$6,448,009

The analysis of different scenarios reveals insights into the EU ETS carbon costs associated with each approach. These costs are closely aligned with the fuel consumption trends observed in each scenario. Notably, scenario 4 stands out with the lowest total EU ETS carbon cost, totaling $6,448,009 over the five-year period, which further reinforces its position as a compelling option for reducing emissions and costs, optimizing operational efficiency. Comparatively, scenario 3 follows with total EU ETS carbon costs of $7,023,216, while scenario 2 incurs $7,783,995, and scenario 1 records the highest total EU ETS carbon costs at $8,901,022.

3.2.5. Total Cost of Ownership and payback period

Table VII details the cost elements for different biofouling management scenarios over a 5-year docking cycle. It is important to note that the calculation of the expected payback period in the table assumes that the same company is the owner and operator of the vessel. This means that fuel costs and the voyage costs are paid by the owner of the vessel.

The TCO for the four biofouling management scenarios provides insights on the financial implications of each option. The initial investment costs, including coating purchase cost and rental of repair yard cost, differ for each scenario. Scenario 4 requires an initial investment of $581,500, while scenarios 1, 2, and 3 have an initial investment cost of $213,500. However, it is important to note that despite the higher initial investment cost of scenario 4, this is quickly compensated due to the increased fuel savings provided by this scenario. Considering the fuel costs, which represent a significant expense, scenario 4 stands out with a total fuel cost of ~$19.950 million. In comparison, scenarios 1, 2, and 3 have total fuel costs of ~$26.70 million, ~$23.85 million and ~$21.80 million, respectively. Moreover, the cleaning costs associated with each scenario should also be considered. Scenario 4 has only propeller polishing costs of $27,000, while scenario 2 incurs $54,000 in cleaning expenses and scenario 3 incurs $210,000, including off-hire costs. Scenario 1 has no cleaning costs.

Table VII: The cost element for different biofouling management scenarios

	Elements of Cost	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 4 VS Scenario 1
Paint	Paint purchasing cost	$62,000	$62,000	$62,000	$305,000	$243,000
Repair Yard	Surface preparation cost	$21,000	$21,000	$21,000	$55,000	$34,000
	Washing cost	$4,500	$4,500	$4,500	$4,500	$0
	Paint application	$12,000	$12,000	$12,000	$65,000	$53,000
	Repair Yard Rent	$30,000	$30,000	$30,000	$40,000	$10,000
	Off hire cost	$84,000	$84,000	$84,000	$112,000	$28,000
Cleanings	Diver cost	$0	$40,000	$140,000	$27,000	$27,000
	Off Hire cost	$0	$14,000	$70,000	$0	$0
Fuel	Fuel Cost (HSFO) 5 Years	$26,700,000	$23,850,000	$21,800,000	$19,950,600	-$6,749,400
	CO_2 emission Tons (HSFO) 5 Years	145,043	129,549	118,425	108,517	-36,526
TCO	**Total Cost of Ownership (HSFO) 5 Years**	**$26,913,500**	**$24,117,500**	**$22,223,500**	**$20,559,100**	**-$6,354,400**
					Savings over 5 years	**$6,354,400**
					Expected Payback Period (Months)	**12**

These findings highlight the significance of evaluating TCO for making informed investments in alternative technologies. While initial investment costs are important, the long-term operational costs, particularly fuel costs, play a crucial role. Although scenario 4 requires a higher initial investment, its lower fuel costs and absence of hull-cleaning expenses contribute to its favorable TCO. The findings also reveal that opting for Scenario 4 over Scenario 1 leads to an impressive payback period of 12 months which may be even shorter for other vessel types and trading patterns. This shows that within just a short timeframe, the accumulated savings in fuel costs from the enhanced fuel efficiency of scenario 4 will recuperate the upfront investment. This underscores the importance of considering the costs across the product lifecycle and making informed decisions to achieve both financial savings and substantial reduction in GHG emissions in the long run.

Note that Table VII does not consider the potential savings from EU ETS carbon costs. Tying together data from Table VI and Table VII, we can gain a more complete picture for difference in through-life costs associated with biofouling management strategies as shown in Table VIII.

Table VIII: The cost element for different biofouling management scenarios

	Elements of Cost	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 4 VS Scenario 1
TCO	Total Cost of Ownership	**$26,913,500**	**$24,117,500**	**$22,223,500**	**$20,559,100**	**-$6,354,400**
EU ETS Carbon Cost	Total EU ETS Carbon Cost	**$8,901,022**	**$7,783,995**	**$7,023,216**	**$6,448,009**	**-$2,453,013**
Total	TCO + EU ETS Carbon Cost	**$35,814,522**	**$31,901,495**	**$29,246,716**	**$27,007,109**	**-$8,807,413**

Taking a comprehensive view, combining the total cost of ownership (TCO) and the EU ETS carbon cost over a 5-year horizon further substantiates the advantage for scenario 4. The total financial outlay and environmental impact are both markedly reduced in this scenario. Specifically, scenario 4 stands out with a combined TCO and EU ETS carbon cost totaling approximately $27.01 million, revealing an impressive cost savings of approximately $8.81 million compared to scenario 1. This analysis underscores the pivotal role of both effective biofouling management strategies and conscientious decisions regarding coating systems in achieving substantial financial benefits while contributing positively to environmental sustainability.

4. Conclusions and discussion

This study introduces a comprehensive framework to evaluate ship energy efficiency measures, considering operational, regulatory compliance, technoeconomic, and environmental aspects. The methodology outlined covers dry-docking and operational phases, offering a well-rounded analysis. A case study utilizing a bulk carrier was conducted to demonstrate the application of the framework with a particular emphasis on biofouling management.

Applying the framework to different biofouling management scenarios for a bulk carrier over a 5-year docking cycle yielded valuable insights into financial and environmental outcomes for each option. The findings underscore the significance of weighing the total cost of ownership (TCO) and the carbon intensity indicator (CII) when choosing biofouling management strategies. This approach aligns with industry needs and environmental targets, guiding informed decision-making for energy efficiency enhancements and emission reductions.

In terms of required power increase, the study revealed that the choice of biofouling management scenarios significantly impacts vessel power requirements. The use of SPC without cleaning resulted in the highest power increase, reaching up to 45% over the 5-year operation. On the other hand, scenarios involving responsive and regular cleaning regimes demonstrated immediate drops in power requirements upon the application of cleaning activities which underlines that in-water hull cleaning is a critical activity in biofouling management. With the use of a silicone-based low friction coating we observed the most favorable results, with an initial power gain (reduction in the required power) and a slow deterioration over time. These findings emphasize the importance of selecting biofouling management options that minimize power increase and improve fuel efficiency.

The cumulative fuel consumption analysis further highlighted the significant fuel-saving potential of different biofouling management scenarios. Among the scenarios involving SPC coatings, the study showed that the use of regular cleaning measures (scenario 3) resulted in the lowest cumulative fuel consumption over the 5-year operation, reducing fuel costs by approximately $4.9 million compared to the scenario 1. However, it is important to note that when comparing across all scenarios, the adoption of a silicone-based low friction coating demonstrated even greater fuel savings. This scenario showcased the lowest cumulative fuel consumption, with a reduction of approximately $6.75 million compared to the scenario 1, namely ‘SPC - no in-water cleaning’. These findings underscore the substantial impact of biofouling management strategies on fuel efficiency and the potential for significant cost savings over the docking cycle. While the scenario 3 is the most favorable among the SPC-based options, the overall silicone-based coating offers the greatest fuel-saving advantage, while also requiring no hull cleaning by design.

The CII analysis provided insights into the environmental impact of the different biofouling management scenarios. The study demonstrated that the scenario involving a silicone-based low friction coating consistently achieved lower CII values compared to other scenarios, indicating improved energy efficiency and reduced carbon emissions. Conversely, scenario 1 (SPC - no in-water cleaning), scenario 2 (SPC + responsive cleaning) and scenario 3 (SPC + regular cleaning) exhibited higher CII values, indicating lower energy efficiency and higher environmental impact. Similarly, the analysis links EU ETS carbon costs with fuel consumption patterns across scenarios, with scenario 4 exhibiting the lowest total EU ETS carbon cost over five years, endorsing its cost-reduction potential. Scenarios 3, 2, and 1 follow with increasing EU ETS costs. These findings emphasize the importance of selecting biofouling management options that not only achieve fuel savings but also align with established and new energy efficiency standards, environmental regulations, and financial implications.

Considering TCO, which includes both the initial investment costs and the operational costs over the 5-year docking cycle, the study revealed that the selection of biofouling management scenarios can have significant financial implications.

Table IX: A qualitative summary of the study's outcomes (★ denotes the least favorable scenario and ★★★★ denotes the most favorable scenario across different perspectives)

Perspective	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**
Power penalty over time	★ Highest due to the fastest rate of degradation over time.	★★ 2nd-highest. The rate of degradation over time is identical to scenario 1 but immediate drops in power requirements occur upon the application of cleaning measures.	★★★ 3rd-highest. The rate of degradation over time is identical to scenario 1 but immediate drops in power requirements occur upon the application of cleaning measures.	★★★★ Lowest due to the slowest rate of degradation over time.
Total fuel consumption	★ Highest. In line with the highest power penalty over time.	★★ 2nd-highest. In-line with the power penalty over time and the number of cleaning applications.	★★★ 3rd-highest. In-line with the power penalty over time and the number of cleaning applications.	★★★★ Lowest due to the 8.5% (2.5% + 6%) out of dock power-gain and slowest rate of degradation (1.4% speed loss) over time.
CII	★ Highest at the end of the cycle. In line with the highest fuel consumption.	★★ 2nd-highest at the end of the cycle. In line with the fuel consumption.	★★★ 3rd-highest at the end of the cycle. In line with the fuel consumption.	★★★★ Lowest due to the lowest fuel consumption.
Total EU ETS carbon cost	★ Highest. In line with the highest total fuel consumption.	★★ 2nd-highest. In line with the total fuel consumption.	★★★ 3rd-highest. In line with the total fuel consumption.	★★★★ Lowest due to the lowest fuel consumption.
Upfront investment cost	★★★★ Lowest due to the low cost of purchasing paint (SPC), surface preparation and paint application.	★★★★ Lowest due to the low cost of purchasing paint (SPC), surface preparation and paint application.	★★★★ Lowest due to the low cost of purchasing paint (SPC), surface preparation and paint application.	★ Highest due to increased cost of purchasing paint, surface preparation and paint application.
Cleaning cost	★★★★ Lowest due to no in-water cleaning applications.	★★ 2nd-highest due to responsive cleaning (hull & propeller) operations (2 times).	★ Highest due to regular cleaning (hull & propeller) operations (7 times).	★★★ Very low due to virtually zero hull cleanings required to maintain the guaranteed speed loss. Only propeller polishing is considered.
TCO	★ Highest driven by the highest total fuel consumption.	★★ 2nd-highest. In line with the total fuel consumption.	★★★ 3rd- In line with the total fuel consumption.	★★★★ Lowest driven by the significant fuel cost reduction. Payback in 12 months.
Overall evaluation of scenarios	★	★★	★★★	★★★★

While the initial investment costs varied among the scenarios, the long-term operational costs, particularly fuel cost, played a crucial role in determining the overall TCO. The scenario involving a silicone-based low friction coating demonstrated the most favorable TCO, considering the lower fuel costs. This highlights the importance of taking a holistic approach when evaluating the financial implications of biofouling management strategies and considering the long-term operational savings.

Table IX presents a qualitative summary of the study's outcomes, utilizing ★ to denote the least favorable scenario and ★★★★ to signify the most favorable scenario across different perspectives.

In conclusion, the case study and analysis utilizing the proposed framework provide valuable insights for ship owners and operators in making informed decisions regarding biofouling management strategies. The study highlights the importance of considering both financial and environmental factors when selecting options. The findings underscore the significant impact of biofouling management choices on fuel efficiency, cost savings, and environmental sustainability. Ship owners and operators are encouraged to assess the specific characteristics of their vessels and operational profiles in order to select the most suitable energy efficiency measures including biofouling management strategies that optimize the total fuel consumption, total cost of ownership, and comply with energy efficiency standards and regulations.

Consideration should be given to the fact that enhancing a ship's technical performance offers a dual advantage. On one hand, it appeals to owners seeking a commercially appealing vessel, while on the other, it brings operators both fuel savings and the prospect of future reductions in EU ETS carbon costs. This convergence of interests is fostering an increasing willingness among operators to invest in coating upgrades and other energy efficiency measures, thereby establishing a 'win-win' scenario that breaks the pre-CII era's split incentive. For the current study, we have operated under the assumption that ownership and operation of the vessel are integrated, with the owner covering fuel and voyage costs. Nevertheless, the adaptability of the developed framework enables the exploration of investment scenarios that involve operators, necessitating customized analysis and result interpretation.

Future pieces of work could involve evaluating the combined effect of energy-saving devices and biofouling management strategies using the developed framework, as well as validating the current findings through the analysis of high-frequency ship data.

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Voyage Optimization Integrating Automatically Collected Data

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Abstract

This paper describes an approach for increased efficiency from voyage optimization through automated integration of advanced vessel performance. Key parts of the approach are: (1) ship-specific vessel performance model for fuel consumption both in design and actual condition, based on data collected during vessel operation; (2) novel routing algorithm allowing variations in physical route and engine power variations; (3) highly automated user interface. This paper presents application experience quantifying saving potential with respect to costs and emissions (CII).

1. Introduction

Data sharing across products often presents friction due to conflicting interests or competing user offers. Vessel owners and operators apply an array of services with different purposes in focus. While these services may individually possess unique features and benefits, cross-platform benefits are rarely utilized. A consolidated data base presents an opportunity for focused expert services to work in symbiosis increasing the informed decision-making foundation and improving the readily available operational and performance potential for the individual services.

Through a collaborative effort Danish based Optimum Voyage and Polish based Enamor are working towards bridging the gap between Vessel Performance and Voyage Optimization. Through API connection voyage optimization is made accessible for autonomous integration as a natural extension of the present decision support platform offered by Enamor. Consumption models generated though data collection, filtration, and analysis are integrated into the voyage optimization engine enhancing optimization potential. Results from the optimizations are delivered and displayed through SeaPerformer allowing for direct and cohesive information flow.

2. Service arrangement

As for the data flow between two systems (SeaPerformer and Optimum Voyage Optimization Server) flow chart Fig.1 represents this process.

The optimization process starts with collecting data about a selected voyage and all the parameters required by the OV API. Once everything is filled in by the user (or left default) and validation passes, a first request is sent to the OV API, to create an optimization job in their system, for future reference. Each response can indicate success or error. In case of an error the data flow goes back to previous step as shown on the flow chart. If the request passes, SeaPerformer receives a created job identifier for monitoring purpose. Error handling is in place in case of any malfunctions. Each successfully initiated route optimization job is saved in SeaPerformer database so the user can see history of the requested optimizations as well as status of optimization job which is updated in intervals. An optimization duration varies depending on several factors, so SeaPerformer is constantly checking for update. Once the route is optimized and job finished, the user receives email notification and is able to see all the optimized route variations in the system as shown in Fig. 6.

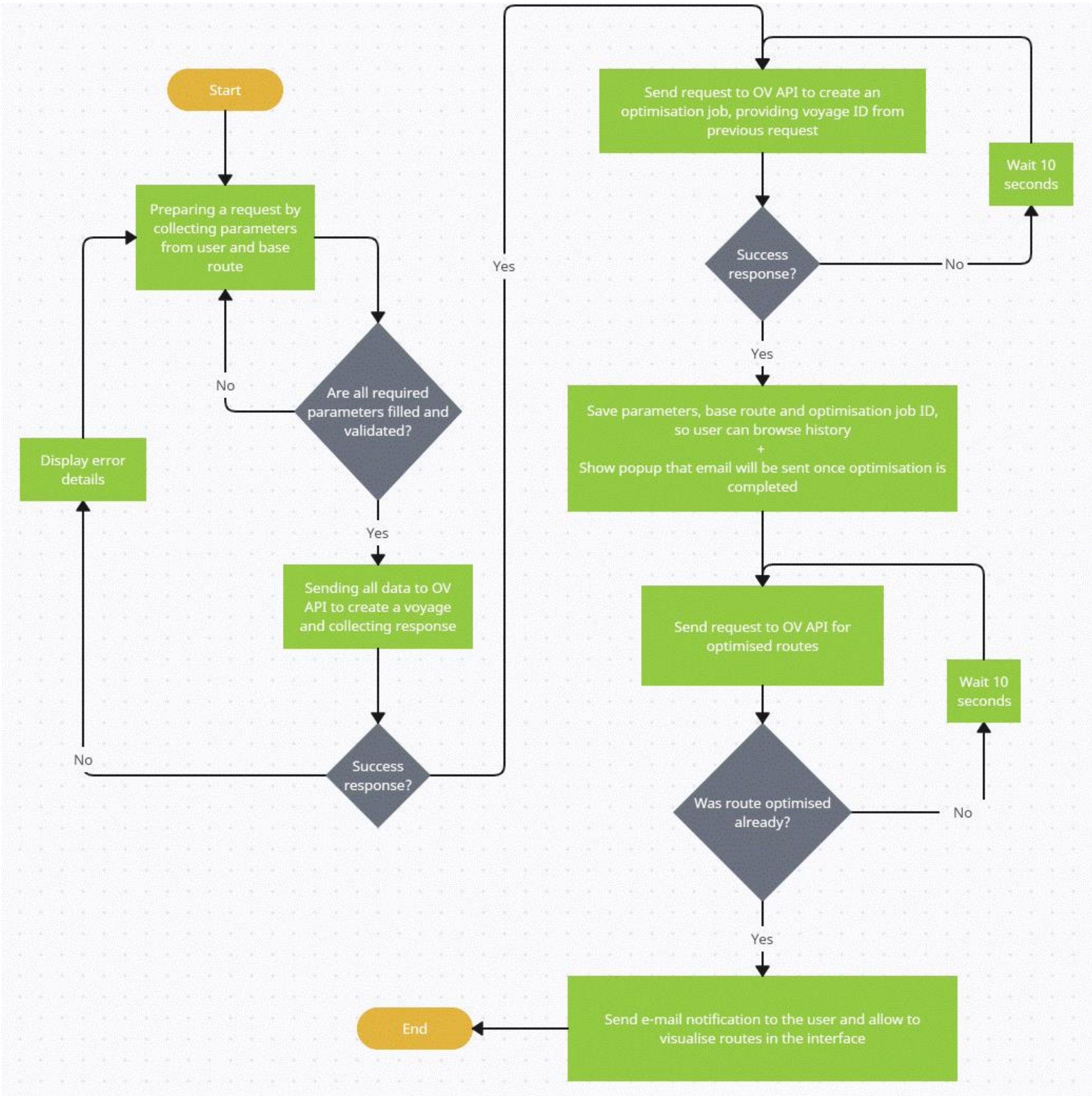


Fig. 1: Data flow chart for SeaPerformer and OV

2.1. SeaPerformer data collection

SeaPerformer is the general, flexible data collection system developed by Enamor and devoted to monitoring of ship operations. It is designed as a modular system therefore it can be adjusted to specific arrangements of the vessel. SeaPerformer is comprised of:

- PC Unit with UPS used as data server, processing unit and ship-to-cloud communication service,
- Multiple Data Collecting Units, data gateways featuring variety of data interfaces and flexible power supply options (230VAC/24VDC),
- Data processing onboard software and user interface providing continuous data validation, visualization and process optimization,
- Data analytics cloud software featuring fleet and vessel operation insight and multiple optimization schemes including route optimization endpoint.

2.2. Minimum dataset

Performing ship routing tasks requires that the optimization algorithm is provided with ability to predict fuel consumption in various operational conditions. The prediction process is based on the performance models which shall adequately reflect impact of ship operational parameters and conditions on the fuel consumption of main consumers used onboard. Preparation of the performance models requires gathering of a dataset upon which models are adjusted or tuned. For this purpose data shall be collected in a consistent manner (i.e. using common time reference and sampling) in order to properly represent correlations. Data collection in a consistent way is the primary task of SeaPerformer onboard system. Following quantities are usually collected during vessel operations for this purpose:

- Fuel consumption of main consumers onboard,
- Load and (optionally) revolutions of main and auxiliary engines,
- Vessel speed through water and over ground,
- Vessel draft and trim (dynamic and static),
- Vessel heading and course over ground,
- Apparent wind speed and direction,
- Air temperature and pressure,
- Wave significant height, direction, and period,
- Water depth,
- Water temperature.

It is nearly impossible to collect the entire set of data using onboard sensors therefore SeaPerformer employs a blending technique incorporating direct measurements and supplementary data sources such as weather, oceanographic and bathymetry services.

2.3. Data validation

Any larger dataset inevitably contains errors and therefore data validation is an essential and crucial process which shall precede any further data analytics. It is especially important while attempting to create the model based on data collected in highly uncontrolled conditions (measurements onboard the ship are far more vulnerable to errors comparing to laboratory measurements). Data gathering based on onboard sensors may include errors due to multiple reasons. The most obvious and common is sensor malfunction. Measurement sensors failure may be manifested by lack of signal accompanied (sometimes) with error indication. Such situation can be easily handled however many data sources may provide a formally valid signal even during malfunction. Many older, but still used, sensors do not provide internal validation and error indications. For such cases more sophisticated methods of data validation are required. Another frequent source of data corruption is sensor misconfiguration. It typically affects analogue measurements for which sensor input (usually voltage or current) require conversion to physical units. Signal processing (sometimes referred to as scaling) is set up during data collection system commissioning and may lead to errors especially in cases where variable input is not available (commissioning is usually done in port or during ship overhaul when some systems are not operational). Data validation can be done on the entire dataset prior to analyses (passive validation) or each time a new data record is collected (active validation). The latter approach is more effective since data analyses usually cover long periods of time and therefore data validation problems undetected at the time of data collection may results in rejection of large parts of the dataset. SeaPerformer provides active data validation with use of simple and sophisticated methods. Among the simple methods there are gap and out-of-range detection. More sophisticated methods compare current measurements with historical trends, reference models or correlated signals in order to detect possible errors. Each time a validation case is detected the ship crew is alerted in order to directly trigger resolution of the problem. The alert flag is stored in the database as to identify the invalid portion of data. An alert status is also sent to the cloud as to increase awareness of the shore personnel.

Some sensors exhibit signal instability in time, so called signal drift. Signal drift results in a shift of sensor's zero level and therefore the same value of analysed quantity will be measured on different levels after sufficiently long time. Signal drift should be diligently taken into account when analysing slow-changing phenomena such as hull fouling. Sensors especially vulnerable to drift are those based on strain gauges (e.g. some types of shaft torque meters) and therefore need frequent recalibration (i.e. adjustment of zero level). Although detection of signal drift exceeds the scope of data validation, SeaPerformer provides functionality which helps mitigate the problem. Time counters, which alert ship crew and notify office team when sensor recalibration is needed can be efficiently used to minimize the risk of significant sensor drift.

Another source of discrepancies, sometimes overlooked, results from sensor operation at low end of their operational range. Sensor's error is usually provided with reference to its full scale (and described as % of FS). Therefore measurements of small values comparing to sensor full scale may result in significant errors. Furthermore sensor's resolution should be also considered. Low sensor resolution (i.e. inability to present small changes of measured phenomena) makes it impossible to represent real dynamics of measured quantities. Although such discrepancies are beyond the data validation process they can be minimized by proper selection of measurement sensors. Analyses of available data sources is provided as the engineering package together with SeaPerformer system delivery. Enamor's experienced support team verifies available data sources with respect to measurement range, resolution, and overall applicability for performance monitoring.

2.4. Performance models

As for the purpose of voyage optimization performance models shall properly describe ship's fuel consumption in various operational conditions. It is crucial to adequately reflect realities of vessel operation in performance models as they constitute the connection between general voyage optimization algorithm and specific operational characteristics of the vessel. If the model fails to adequately describe vessel performance, the resulting route will be formally optimum but purely artificial as developed for the "vessel" of different characteristics. A route determined with use of inadequate performance models does not utilize the optimization potential to the full extend and results in higher operational and environmental costs. SeaPerformer uses decomposed performance models. Decomposition concerns main fuel consumers onboard and operational conditions:

- Main engine(s) fuel consumption with respect to:
  - Calm weather and unrestricted waters – reflecting impact of ship speed through the water, draft and trim,
  - Wind – reflecting impact of apparent wind speed and direction as well as air physical properties,
  - Wave – reflecting impact of significant wave height, direction and period (separately for wind and swell waves, subject to data availability),
  - Current – reflecting impact of course corrections,
  - Water depth – reflecting impact of sea bed vicinity,
  - Water physical properties – reflecting impact of water salinity and temperature
- Auxiliary engines fuel consumption separately determined for:
  - Port operations,
  - Transit,
- Boilers (not used for route optimization),

In case of main engines, the performance models describe amount of power required to maintain vessel operation at given conditions. For the purpose of voyage optimization, where fuel consumption is needed, it is calculated with use of specific fuel oil consumption (SFOC) based on engine manufacturer data and corrected for engine wear, *Górski et al. (2020)*.

Preparation of performance models is the process which undergoes in stages. Although some parts of it could be automatized it still requires attention of experienced data analysts due to unstructured and non-standardized nature of input data. The process starts with gathering of reference data and information which helps to understand what the vessels technical characteristics are. Typically design and delivery documentation is used at this stage. These documents include: general arrangement plan, hydrostatics and stability booklets, propeller and rudder design, results of model tests and numerical analyses, engine shop tests and ship sea trials. The information has different formats highly depended on the shipbuilder and model testing facility practice and therefore requires special attention in digitalization as to maintain compatibility with data collected onboard. Reference data may include ship powering characteristics in a form of power-speed curves. These datasets are especially convenient since usually describe vessel performance in large range of speeds, drafts and sometimes for different trims. However, they must be used with care since power estimates may contain significant errors. For these reasons design data shall be validated against sea trials results for compliance at design point (design speed and draft). Furthermore, one shall take into account that, due to limitations of model testing processes, power predictions at low speeds may contain larger errors. Due to above reasons performance models developed based on reference data require validation and usually some degree of adjustment. It starts with selection of a characteristic period of operation for which vessel performance may be considered as reference. Three to six months period following ship delivery or hull cleaning is usually feasible for the purpose. It is sufficiently long for the vessel to operate in different conditions (large variation in speeds and drafts improves applicability of the model) and is for most cases uniform in terms of hull fouling impact (performance in reference period shall be stable). Data taken from the reference period requires preparation. First, the dataset is checked for completeness. In case of data gaps, subsidiary data sources (weather, bathymetry etc. services) may be used. Secondly, the dataset is cleaned for outliers and non-stationary conditions. Lastly, extreme weather (wind and waves) and navigation (shallow waters) conditions are filtered out. Remaining data is corrected to standard conditions (calm weather, unlimited waters) and constitute the reference dataset for validation of the performance model. Validation consists of calculation of the power increase in reference period with respect to the performance model. Resulting power increase should be small and consistent along entire reference period. Any larger deviation indicates deficiency of the reference model which requires adjustment. Up to the time of writing the paper, model adjustments are performed manually but automatization of the process is subject of the planned research.

In case power-speed curves are not available, the performance model can be prepared directly from data collected in the reference period. Methods implemented by *Gorski et al. (2021)* or *Berthelsen and Nielsen (2022)* have been successfully used for the purpose. However, due to limitations of the data set, performance model received with use of collected data only suffer due to lower range of speeds and drafts.

The last part of performance model preparation consists of defining impact of environmental and operational conditions. As the reference methods the following are implemented:

- Wind – *ITTC (2021)*,
- Wave – *Tsujimoto and Orihara (2019)*,
- Current – own method based on the centroid drag in oblique flow,
- Water depth – *Raven (2021)*,
- Water physical properties – *ITTC (2021)*

Within IVO project Enamor develops adjustment algorithm for tuning of above methods as to better reflect vessel characteristics with respect to environmental impact. Works are based on tunning method developed earlier for the purpose of calm water performance modelling, *Górski (2016)*. Advances in the subject will be reported in future editions of HullPIC conference.

In parallel to the main engine fuel consumption model, one for auxiliary engines consumption is created. Auxiliary engine fuel consumption is modeled as the function of time but separately for port and transit operations. The same method as developed earlier for the purpose of CII is implemented *Górski et al.*

(2022).

2.5. User interface and OV API connection

Route optimization service has been included in the SeaPerformer user interface. It consists of three subpages. Route finder, Fig.2, allows for approximation of ship track and is used for further optimization. On the left side, there is a list of waypoints which are to be visited by the vessel. There can be more than two (as presented in example). Adding a waypoint can be done by “Add waypoint” button, and then searching a port by a name, code, or country, or can be also selected directly from the map. There are additional parameters such as speed, draft, trim, used fuels, and departure time and few other used less frequently. All those parameters are taken into account when selecting an initial route between ports.

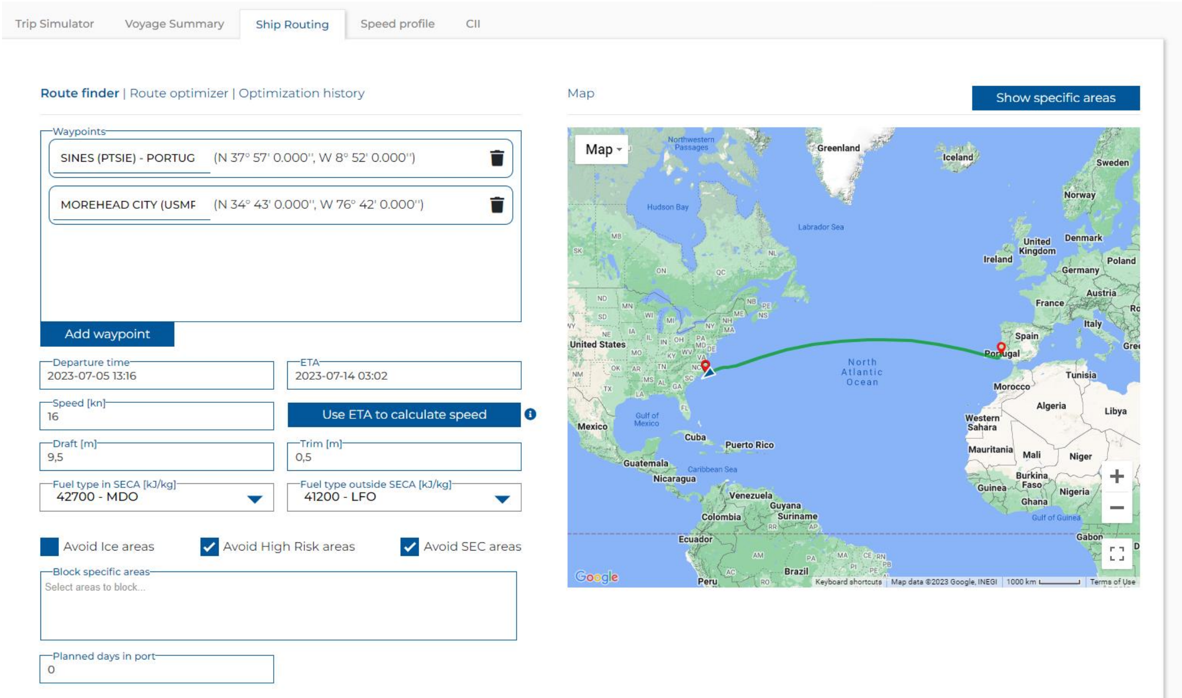
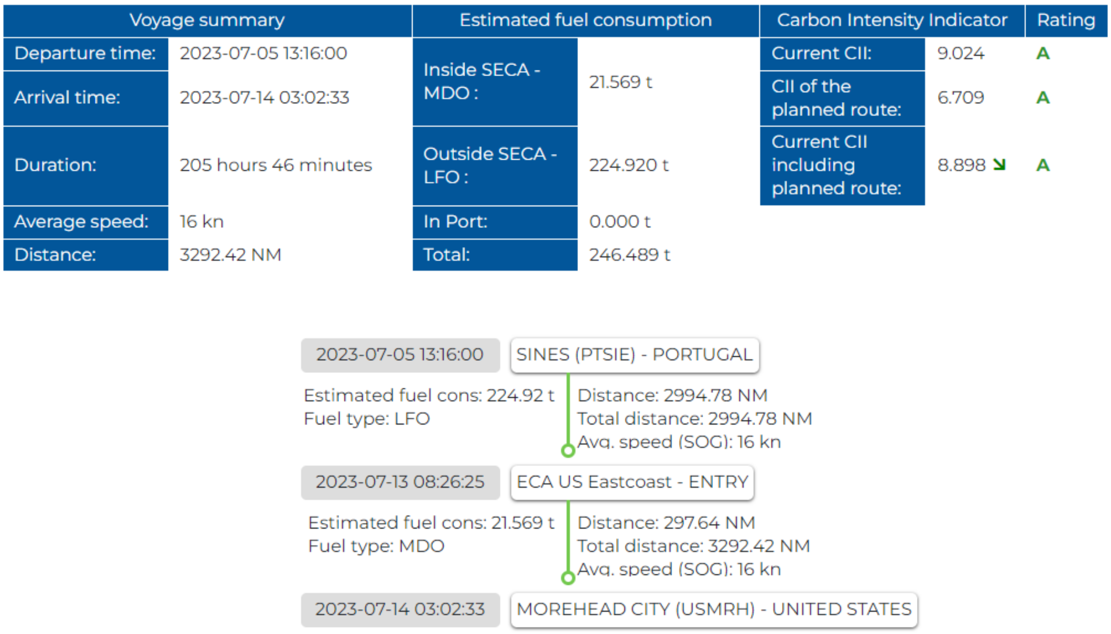


Fig.2: Main view of SeaPerformer when planning a route



Voyage summary		Estimated fuel consumption		Carbon Intensity Indicator		Rating
Departure time:	2023-07-05 13:16:00	Inside SECA - MDO :	21.569 t	Current CII:	9.024	A
Arrival time:	2023-07-14 03:02:33			CII of the planned route:	6.709	A
Duration:	205 hours 46 minutes	Outside SECA - LFO :	224.920 t	Current CII including planned route:	8.898 ↘	A
Average speed:	16 kn	In Port:	0.000 t			
Distance:	3292.42 NM	Total:	246.489 t			

Fig.3: Additional information and voyage tree

As soon as an initial route is available additional information is presented in a form of voyage summary Fig.3. It contains departure and arrival time, counted duration of the voyage and the distance. Additionally, information about fuel consumption and CII is included. There is also a "voyage tree" which contains details divided into voyage legs.

After the initial route is found, a second tab becomes active which is the "Route optimizer" Fig.4. As the name says this tab contains a few additional parameters needed for the optimization, such as fuel and charter costs, and optimization type. As soon these parameters are provided the user can initiate optimization process.

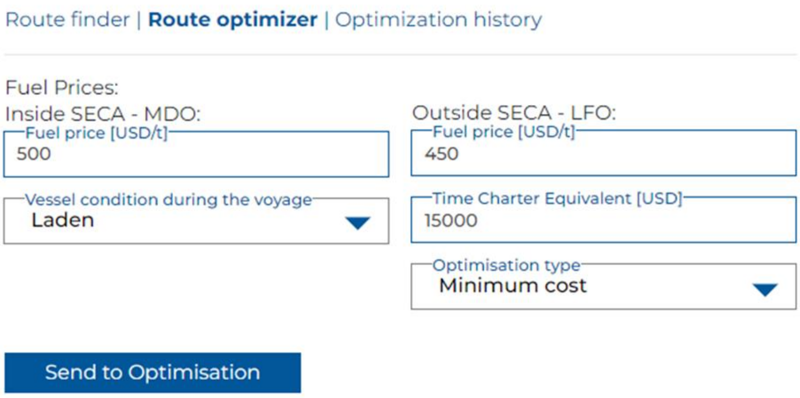


Fig.4: Parameters needed for the optimization

It involves interoperation between SeaPerformer and OV routing system and is asynchronous. Therefore the user is informed about the successful initiation of the process (i.e. input data comply with OV requirements). The route optimization process is monitored by SeaPerformer. As soon as results are available they appear in Optimization History section Fig. 5. Email notification is send in parallel.

Route finder | Route optimizer | **Optimization history**

	Date	Departure	Destination	Job Status
	2023-06-16 07:48:18	LISBOA (PTLIS) - PORTUGAL	LEONARDO (USDOJ) - UNITED STATES	complete
	2023-06-19 11:23:06	GDYNIA (PLGDY) - POLAND	STURA (NOSTU) - NORWAY	complete
	2023-07-05 11:41:02	FIGUEIRA DA FOZ (PTFDF) - PORTUGAL	EDGARTOWN (USETW) - UNITED STATES	

Load Route

Fig.5: Optimized routes history

The user can select completed optimization job Fig. 6 to be shown on the map on the right. Selecting the job and loading it on the map shows few of the optimized routes to select from. There are few things to have an eye on. ETA, and the duration of the voyage, as much as difference in total costs of selected voyage. Each of those parameters can be important when deciding which route to select.

On the map there is a difference shown between initial route (green) and optimized one (blue) often with visible variations depending on weather and operational parameters.

Route finder | Route optimizer | Optimization history | **Route suggestions**

Map

Show specific areas

				Fuel Consumption		Cost			
Recommend	ETA	Avg. Speed	Duration	Inside SECA	Outside SECA	Fuel	Hire	Total	Difference
BASELINE	2023-06-24 12:16:00	15.947 kn	194h 28min	19.19 t	294.51 t	142122.80	121544.44	263667.24	0.00
SELECTED_AUTO	2023-06-24 11:39:00	16.031 kn	193h 51min	19.45 t	283.73 t	137405.06	121160.94	258566.00	5101.24
ALTERNATIVE	2023-06-24 21:30:00	15.272 kn	203h 42min	18.27 t	261.43 t	126775.61	127317.19	254092.80	9574.44
ALTERNATIVE	2023-06-24 17:39:00	15.543 kn	199h 51min	17.62 t	269.27 t	129979.54	124914.66	254894.20	8773.04
ALTERNATIVE	2023-06-24 13:55:00	15.838 kn	196h 7min	17.82 t	278.30 t	134142.37	122576.30	256718.66	6948.58
ALTERNATIVE	2023-06-24 09:35:00	16.220 kn	191h 47min	17.88 t	291.59 t	140154.56	119873.22	260027.78	3639.46
ALTERNATIVE	2023-06-24 05:40:00	16.551 kn	187h 52min	21.14 t	299.67 t	145424.14	117418.48	262842.62	824.62
ALTERNATIVE	2023-06-24 01:34:00	16.913 kn	183h 46min	17.94 t	317.21 t	151714.29	114854.23	266568.53	-2901.29

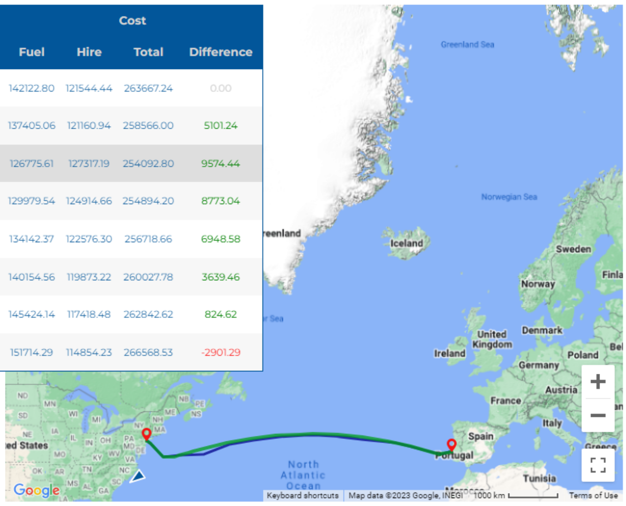


Fig.6: Optimized route details and variations

2.6. Optimum Voyage routing service

Weather routing and voyage optimization are the common terms covering routes generated with the main purposes of avoiding heavy weather and optimizing the commercial outcome through the routing of vessels. Products and services range from low-tech manual route alterations to high-tech algorithm driven solutions. Common for the quality of the generated results is a high dependence to the quality of data fed to the product. Of greatest significance are:

- Weather forecasts
- Current forecasts
- Weather impact on speed or power requirement

- Driving algorithm
- Calm water speed / power or consumption models

While the quality and reliability from weather- and current forecasts are individually expertized fields the remaining elements are fields of scrutiny for the individual routing provider.

Optimum Voyage weather routing approaches the impact of weather as an impact on the effective speed a vessel will achieve. This approach mimics the actual operation of a vessel and thereby results in directly actionable routing options. An engine load is maintained through a specified period and weather impact on speed is calculated as a resulting speed loss from calm water speed. As a vessel would experience a loss of speed while under the influence of seas and wind the same will apply for the evaluation of a voyage where the effective speed also changes the time the vessel will be at the respective positions throughout the route and thereby the sampling of the correct forecasted weather.

The magnitude of the speed loss the vessel experiences can be accounted for in a multitude of approaches – considering Beaufort Scale and Douglas Sea State, applying wave height and wind speed and more. As this weather impact not only is specific to the individual vessel but for waves also varies depending on the relative direction and period, both parameters in combination with the significant wave height are accounted for. The specific influence is modelled with vessel characteristics to compute the resistance incurred from waves. In a similar fashion wind is accounted for by relative direction and wind speed in combination with vessel main characteristics. The added level of detail increases the computation complexity but elevates the precision of evaluated weather impact required for an optimization to fully capture the dimensions of voyage evaluation.

A selection of optimization algorithms is applied in a series of steps for the individual voyage optimization. The optimizations are free to search a non-discretized solution space to not limit to a grid search, where optimization potential is directly coupled to the coarseness of the applied grid. The search for an optimum solution is performed applying a simultaneous local and global search. The local search refines potential best solutions pushing the savings potential while the global search performs a broader search for a potential better alternative solution. This also allows for the algorithms to avoid becoming stuck in local minima or incorrect optimum.

While weather routing has been available for the past decades through alterations of waypoints (latitudes, longitudes), speed / power optimization remains a relatively new discipline to be applied to weather routing and voyage optimization. Adding speed variation either as on fixed power change throughout a voyage or as variable power throughout a voyage adds an additional dimension to the solution space, increasing the potential voyage savings. Although speed/power optimizations are offered as stand-alone services the added dimension is not unlocked unless carried out in combination with the waypoint optimization. This effectively allows for alternate solutions where e.g. heavy weather is not exclusively avoided through waypoint modifications, but also with slowing down and/or speeding up. This also allows a route to not only search for beneficial weather in space, but also in time. The Optimum Voyage optimizations allow for power variations throughout a voyage when applicable to the vessel operation.

2.7. OV API

The Optimum Voyage optimization API has been enabled through the level of automation applied to the core of the algorithmic built of the solution. For a successful approach to an API based solution the full operational flow is required to retain full flexibility while remaining entirely frictionless for the user. This in turn has required all processes to be fully automated.

Once a vessel is activated for API use available vessel characteristics are automatically sourced through the IMO number and the digital vessel model is generated for use in optimizations. The characteristics are used to automatically generate a tailored core consumption model for every vessel, and to generate the models applied to the calculations of added resistance from weather, and lastly to retain information required to evaluate restrictive navigation.

Upon activation an external consumption model for the vessel can be applied through the API. This process is automated in the background and will not require any action from the end user. The external consumption model can at any time be updated through the API which is relevant at any point an improved model is available.

Once a user has planned a voyage, on board or ashore, the voyage can be sent for optimization with applicable voyage specific details. Different optimizations can be selected including: CP optimization, minimum cost optimization, on-time-arrival and more.

Through the optimization run on cloud servers the algorithms ensure that that any planned parts of a voyage through restrictive navigation areas are retained to maintain any planned navigability of the voyage. The servers draw on the latest available weather- and current forecasts along with enhanced AIS to ensure that the results generated are relevant and up-to-date at all times. Once optimization convergence is achieved a route solution is returned to the system calling the API.

The route solution includes an identified best voyage option along with weather optimized alternatives for different arrival times. Every option includes route specifics with waypoints, power / speed settings defined in RTZ-format along with total voyage break down of consumption, costs and time-series weather analysis throughout the voyage.

As weather and actual vessel operation changes day to day users are encouraged to activate a daily optimization to run to ensure the user retains the full savings potential possible throughout the voyage.

2.8. OV Integrated Consumption Models

Allowing cross product integration allows for owners and operators to achieve full benefits from every service application. Clients already accustomed with a specific vessel performance solution relying on data tracked, filtered, and modelled over an extended period, are enabled to allow these models to also form the foundation of the digital vessel model applied in voyage optimization.

A collaborative consumption model format has been developed that allows for integration of calm water performance models, but also models that account for the impact of weather while retaining the detailed weather evaluation. The format is compressed to retain detail while remaining quickly transferable through the API.

The necessity of precise voyage consumption predictions can be debated for specific optimization types, including those requiring a fixed engine load throughout a voyage. The primary objective of such an optimization is minimized fuel consumption, assuming that no unsafe voyage option is produced. As such the analyzed solution space forms the foundation for relative evaluation where any consumption error is carried through all voyage evaluations and the minimum will remain the best solution even with reduced uncertainty. Any such error or uncertainty to speed-power predictions may though not only offset the estimated fuel consumption for a voyage but also effect the anticipated vessel position at a specific time, thereby further shifting sampled weather, thus carrying an accumulated error forward. Results thereby retain a further optimization potential enabled by precise speed-power predictions.

For voyages with flexible arrival time and the ETA decided by a commercial driver, fuel consumption is translated to fuel cost through the applicable fuel prices. Voyage time is similarly translated to time cost through hire rate or TCE. Any offset or uncertainty in the underlying consumption model is carried through to the evaluation of total fuel cost which will impact the indicated least cost arrival time considering both fuel and time. Increasing the prediction accuracy through the integration of a readily available external consumption model will for these instances increase profitability of operation.

2.9. OV Integrated Voyage Optimization

Integrating voyage optimization into the already established platform offered by Enamor allows the user a single access point for informed decision making. As the vessel performance is already present in the systems forming the foundation for multiple commercial decision as well as planning of coming voyages, extending the offering with voyage optimization becomes a natural continuation of the work processes. The user is allowed a cohesive flow of data, analyses, and results to be visualized.

As the requirement for data transfer is at a minimum due to weather forecasts not having to be downloaded locally to the vessel, this can be achieved even at low data access allowing for high-tech voyage optimization on board vessels disregarding available hardware.

The integrated solution based on continuous data collection and periodic re-evaluation of vessel performance takes into account changes of the vessel performance in time due to wear of ship components and degradation of hull surface and therefore provides better modelling of the ship operation and in turn more adequate voyage planning.

3. Results

To illustrate the potential of the optimizations, voyages carried out by three vessels over the course of three months, with a total of 150 voyage days were studied. During the period of analysis, the vessels primarily operated in the Indian Ocean, Atlantic, and the Red Sea with voyage durations ranging 5 to 20 days. All executed voyages were carried out with weather routing already applied by a well-recognized routing provider.

All voyages were analyzed and subsequently re-optimized using two different optimization types:

1. On-time-arrival optimization – where the achieved ETAs from the realized voyages were maintained.
2. Minimum cost optimization – allowing for alternate arrival times based on the commercially best outcome accounting for total fuel and hire costs.

To ensure the results of the re-optimizations remained like-for-like and mimicked the service offered the voyages were re-optimized for every 24 hours passed during the voyages. Every optimization was run using only the weather and current forecasts as they were available at the given time of optimization. It was assumed that the vessel would follow the routing advise provided through the service. Upon finalization the resulting routes were compared through analysis using the same consumption model, and differences in voyage outcomes were compared.

From maintained ETA only the fuel consumption reduction was of relevance as there is zero difference in time spent at sea. An overall fuel consumption reduction of 4.4% was found on top of the already optimized voyages. The total reduction was in excess of 175MT fuel, conversely in excess of 550MT CO_2 showing the savings in operation costs and benefits in terms of emissions. Voyage optimization can be efficiently used for improving the environmental performance of a vessel, also potentially affecting the achieved CII.

For the minimum cost optimization the overall operational costs, considering both fuel and hire, were reduced by a factor 2.7 to the cost savings achieved by maintaining ETA.

4. Summary

The last decade has been a period of incredibly dynamic change in the interest in using data in the maritime industry. Both the scope and frequency of data collection during the operation of ships has increased significantly. Traditional manual data collection has been replaced by automated data acquisition on many vessels in operation. New build projects offered by leading shipyards feature data gathering as a standard. Shipowners have already accumulated a huge amount of data. At the same time, the market of data-based services was developing dynamically. More and more companies offer specialized data processing. However, the use of data to implement the services offered still involves significant effort on the part of the shipowners.

Enamor and Optimum Voyage identified this barrier and initiated collaboration aimed on smooth, automated cooperation between their respective platforms. As a result, voyage optimization services offered by OV have been coupled with SeaPerformer data acquisition and processing platform. Data preparation and exchange has been automated and are executed as background tasks. User involvement was minimized resulting in very intuitive, yet powerful tool. The use of data to create a performance model allows to better reflect the actual characteristics of the ship. As a result, the optimized route is better suited to the technical capabilities of the ship, ensuring lower costs of the transport task. At the same time voyage optimization may be used to reduce environmental impact. It is a great tool to improve emission metrics such as CII.

Acknowledgement

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STW or SOG or as a Starting Point for Performance Modeling? An Empirical Study using Operational Sensor Data from 20 Oil Tankers

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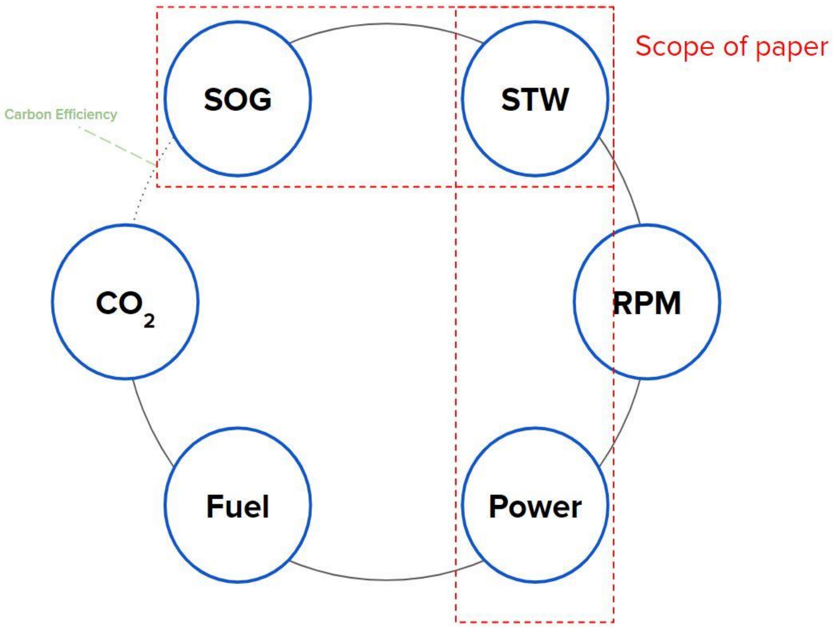
Abstract

This study details data-driven findings based on actual operational high-frequency sensor data of over 20 Crude Oil Tankers owned by Euronav, with the goal to decide between STW (Speed-Through-Water) or SOG (Speed-Over-Ground) as a starting point for accurate ship performance modeling.

1. Introduction

Efficiency gains are the go-to answer to reach short-term decarbonization targets in shipping. To capture these efficiency gains, accurate speed-fuel models of vessels are a prerequisite. The challenge of creating accurate speed-fuel models - also called ship performance models - lies not only in accounting for all the secondary factors influencing this relationship (waves, wind, currents, draft, trim, water depth, etc.), but also in getting accurate data on the crucial variables speed and fuel.

The rise of telemetry equipment and high-frequency data collection on-board vessels has enabled many improvements for ship performance modeling, *DeKeyser et al. (2022)*. Nevertheless, with sensor data an even more critical mindset is necessary to decide what data can be trusted. Especially when it comes to the speed of the vessel, a dilemma often ensues to choose for Speed-Over-Ground (SOG) data based on GPS-location, or to choose for Speed-Through-Water (STW) data based on the speed log.



This study analyzes data of 20 oil tankers (V1-V20), with the purpose of finding a data-driven answer to the above dilemma. Should we use SOG or STW as a starting point for performance modeling? What options do we have and how can we maximize performance modeling accuracy? The 20 vessels are VLCC's and Suezmax's. On average we analyzed 1 year of sensor data for every ship. The data consists of measurements at 5-minute intervals.

2. Difference between SOG and STW

In theory the difference between SOG and STW should only be due to currents. As a result, the following formula is often used to convert SOG into STW:

$$\mathrm{STW} = \mathrm{SOG} + \mathrm{Current\ Speed} * \cos\left(\mathrm{Heading} - \mathrm{Current\ Direction}\right)$$

The factor “current_speed * cos(heading - current_direction)” is also referred to as Current Product (CP), as it represents the vector component of the currents in the direction the ship.

3. Inaccuracies for different SOG to STW models

Put simply, we have two different approaches to calculate the STW:

1. Simple: STW = SOG
2. Current Formula: STW = SOG - Current Product (CP)

For the 20 vessels, this generates the following results, on average.

A table with all 20 ship-specific results can be found in Appendix A.

For more information on the accuracy metrics, please refer to the Blue Modeling Standard, *Deschoolmeester and Morobé (2023).*

Acc. Metric	STW = SOG	STW = SOG - CP
MAPE	6.05%	5.25%
Voyage Error	3.66%	3.73%
R^2	0.65	0.71

Unexpectedly, the second approach with the correction factor for currents barely outperforms the first very simple approach. For the voyage error it even worsens. This means that the Current Product (CP) has very limited explaining power. This is an unexpected finding, as in theory the CP should explain all the differences between SOG and STW.

Given these findings, we might need to reframe the question. Is the approach to predict STW incorrect, or is the value we are trying to predict incorrect? Given the known flaws of speed log sensors to measure STW accurately, *Ikonomakis et al. (2021)*, a likely answer could be that STW values are simply inaccurate.

The second part of this study explores the following hypothesis: if the inaccuracy is really due to inaccurate STW measurements, rather than an incorrect formula to predict STW from SOG, then this will be reflected in end-to-end SOG to Power modeling accuracy. Or in other words, it might be that the formula above predicts close to the ‘true STW value’ of the vessel, but that the measured STW value we validate against is simply inaccurate. If this is true, then if we would predict from SOG all the way to the Main Engine Power of the vessel, it would be more accurate to start modeling from a calculated STW instead of the measured STW. This hypothesis is tested below.

4. Impact of the STW inaccuracies on Speed-to-Power modeling

To validate the hypothesis above, we model the Main Engine Power, starting from SOG in three different ways. All three use the same modeling approach: physics-informed machine learning in

Toqua's proprietary Ship Kernels, *Collé and Morobé (2022)*. The only difference is what version of the STW is used as starting point.

1. Traditional: Measured STW **-** Train Power model starting from measured STW. Generate STW from SOG-CP.
2. Simple: SOG **-** Train Power model starting from SOG. No current corrections, so STW=SOG.
3. Current formula: Calculated STW **-** Train Power model starting from calculated STW = SOG - CP.

It is expected that the closer the approach gets to the 'true STW value', the more accurate the end-to-end SOG→Power model will be. The 'true STW value' is unknown, so the end-to-end speed-to-power accuracy serves as a proxy for which approach is most accurate to predict the 'true STW value'.

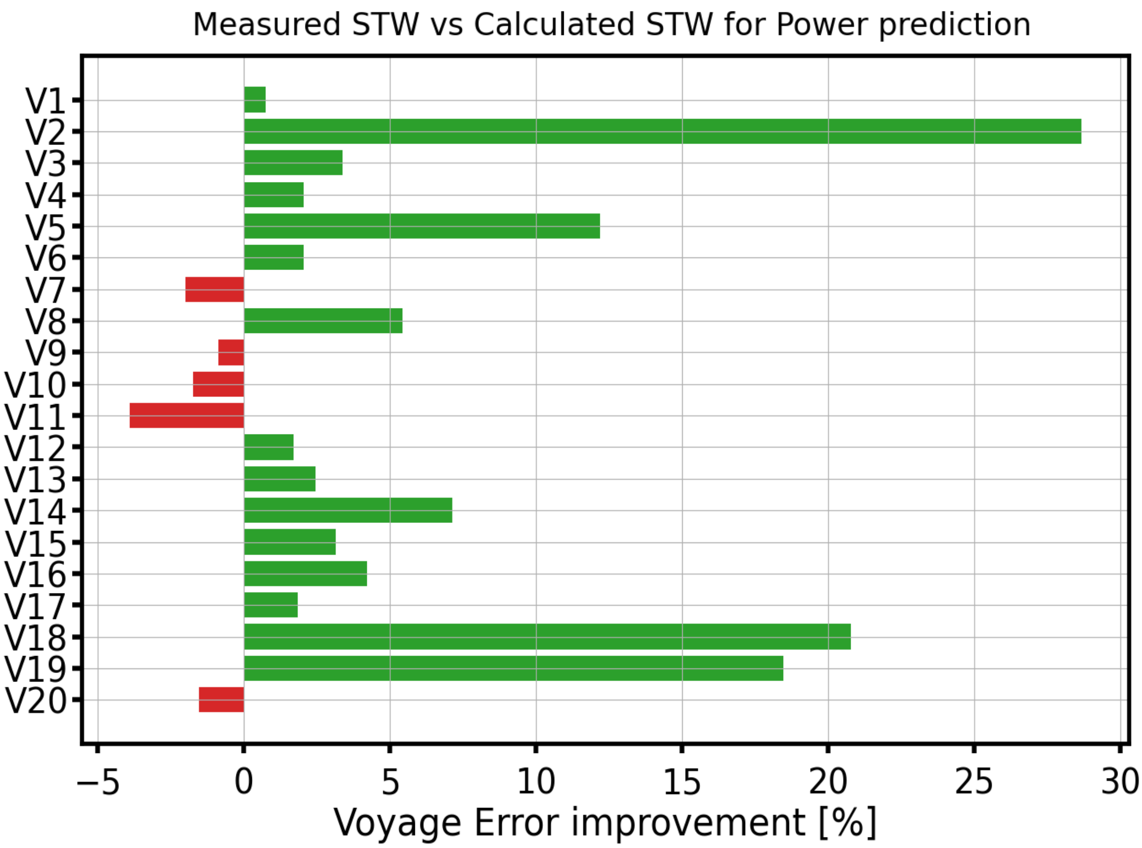
For the 20 vessels and these 3 different starting points, this generates the following results, on average. A table with all 20 ship-specific results can be found in Appendix B.

Acc. Metric	**Measured STW**	**SOG**	**Calculated STW**
MAPE	15.43%	14.15%	11.46%
Voyage Error	8.33%	4.22%	3.12%
R^2	0.49	0.54	0.67

Using SOG instead of measured STW reduces voyage accuracy from 8.3% to 4.2%. Using calculated STW instead of measured STW, reduces voyage inaccuracy from 8.3% to 3.1%.

This confirms the earlier hypothesis. Training a model from the measured STW, leads to large inaccuracies. Much larger than if you would simply take SOG or calculated STW as input. However, most scores for the measured STW scenario are not that much worse than the other scenarios. It is just that some vessels (V2, V5, V14, V18, V19) have exceptionally large voyage errors for the measured STW scenario (12%-32%); as a result the measured STW scenario drastically underperforms on average. This is caused by inaccurate speed logs, which are drastically more erroneous on some ships than on others. This confirms the hypothesis that measured STW values are often less accurate than calculating STW starting from SOG. This was proven indirectly by using end-to-end speed-to-power modeling accuracy as a proxy.

In some cases (V7, V9, V10, V11, V20) the measured STW scenario outperforms the other scenarios. This indicates that in some cases the STW does capture meaningful information that goes beyond what SOG and correction factors can account for. We believe these cases have highly accurate and well-calibrated speed logs. But they are the exception, not the rule.



5. Conclusion

After analyzing operational sensor data for 20 oil tankers, to analyze if SOG or STW is the best starting point for accurate performance modeling, we find that measured STW values are unreliable. Using them leads to large average inaccuracies for performance modeling (8.3% voyage error). Instead, using the more reliable SOG, already reduces the voyage error to 4.2%. If we then go a step further, and not simply use SOG, but apply corrections factors for currents to derive a calculated STW, the voyage inaccuracy further reduces to 3.1%. By using end-to-end modeling as a proxy, these numbers indirectly confirm the hypothesis that STW sensors are unreliable. The most robust estimation of the true STW value is found via a formula based on SOG and currents, rather than measurement devices.

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Appendices

A) SOG-STW table for all 20 vessels

i. MAPE

Vessel	SOG=STW MAPE	Current formula MAPE
V1	4.33%	4.02%
V2	10.17%	9.81%
V3	6.86%	5.99%
V4	5.68%	5.09%
V5	6.77%	5.37%
V6	5.53%	4.11%
V7	5.74%	3.97%
V8	5.01%	3.80%
V9	3.52%	3.23%
V10	3.84%	3.55%
V11	6.66%	5.47%
V12	3.96%	3.09%
V13	4.07%	3.59%
V14	10.23%	9.38%
V15	5.15%	4.14%
V16	5.06%	4.41%
V17	5.36%	4.61%
V18	8.88%	8.68%
V19	10.91%	9.65%
V20	3.18%	2.97%
Average	6.05%	5.25%

ii. Voyage Error

Vessel	SOG=STW Voyage Error	Current formula Voyage Error
V1	1.59%	2.37%
V2	9.93%	10.61%
V3	3.38%	3.90%
V4	3.44%	3.81%
V5	3.44%	4.05%
V6	1.41%	1.21%
V7	1.11%	0.68%
V8	1.99%	2.28%
V9	1.06%	0.89%
V10	0.97%	0.93%
V11	4.23%	3.47%
V12	1.70%	1.16%
V13	2.37%	1.65%
V14	9.64%	9.92%
V15	2.38%	2.45%
V16	1.78%	2.71%
V17	3.49%	2.82%
V18	7.98%	8.94%
V19	9.56%	9.59%
V20	1.72%	1.23%
Average	3.66%	3.73%

iii. R^2

Vessel	SOG=STW R^2	Current formula R^2
V1	0.76	0.80
V2	-0.21	-0.11
V3	0.48	0.62
V4	0.65	0.73
V5	0.60	0.77
V6	0.76	0.88
V7	0.78	0.90
V8	0.77	0.88
V9	0.82	0.88
V10	0.77	0.83
V11	0.55	0.71
V12	0.68	0.83
V13	0.81	0.86
V14	0.34	0.45
V15	0.66	0.78
V16	0.66	0.77
V17	0.73	0.81
V18	0.45	0.49
V19	-0.65	-0.21
V20	0.83	0.83
Average	0.65	0.71

B) SOG-Power table for all 20 vessels

i. MAPE

Vessel	Measured STW MAPE	SOG MAPE	Calculated STW MAPE
V1	10.39%	12.05%	10.84%
V2	32.23%	12.52%	9.80%
V3	12.97%	13.22%	9.57%
V4	12.69%	13.37%	10.54%
V5	21.97%	18.36%	15.98%
V6	12.30%	19.32%	11.50%
V7	12.42%	18.81%	12.71%
V8	12.94%	18.64%	11.77%
V9	12.01%	14.11%	12.96%
V10	12.60%	14.27%	12.91%
V11	11.27%	11.29%	10.16%
V12	8.76%	10.08%	8.74%
V13	11.19%	11.32%	9.99%
V14	22.26%	15.44%	13.14%
V15	14.12%	14.35%	11.39%
V16	13.56%	13.35%	12.13%
V17	14.50%	14.53%	12.20%
V18	26.61%	15.96%	12.60%
V19	23.77%	10.58%	9.52%
V20	10.02%	11.41%	10.70%
Average	15.43%	14.15%	11.46%

ii. Voyage Error

Vessel	Measured STW Voyage Error	SOG Voyage Error	Calculated STW Voyage Error
V1	3.48%	3.48%	2.74%
V2	32.19%	4.76%	3.51%
V3	3.71%	0.05%	0.32%
V4	5.74%	4.03%	3.70%
V5	18.20%	5.78%	5.99%
V6	4.44%	8.16%	2.40%
V7	2.12%	8.54%	4.12%
V8	7.76%	5.11%	2.32%
V9	4.15%	5.42%	5.02%
V10	4.90%	8.47%	6.63%
V11	1.41%	2.27%	5.33%
V12	1.83%	1.18%	0.14%
V13	3.75%	0.37%	1.31%
V14	11.85%	6.59%	4.72%
V15	5.54%	2.28%	2.39%
V16	4.74%	2.75%	0.53%
V17	6.06%	6.16%	4.22%
V18	22.70%	2.19%	1.91%
V19	21.32%	4.64%	2.85%
V20	0.77%	2.11%	2.31%
Average	8.33%	4.22%	3.12%

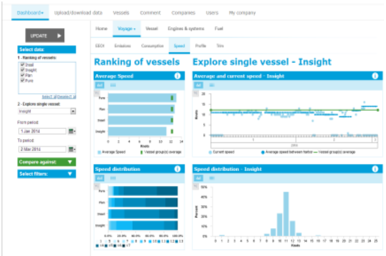
iii. R^2

Vessel	Measured STW R^2	SOG R^2	Calculated STW R^2
V1	0.29	0.31	0.37
V2	-0.19	0.82	0.87
V3	0.70	0.75	0.82
V4	0.75	0.67	0.80
V5	0.16	0.57	0.63
V6	0.79	0.58	0.84
V7	0.76	0.59	0.78
V8	0.75	0.61	0.83
V9	0.46	0.21	0.42
V10	0.63	0.57	0.65
V11	-0.01	0.13	0.37
V12	0.40	0.29	0.54
V13	0.86	0.86	0.89
V14	0.14	0.34	0.52
V15	0.72	0.70	0.81
V16	0.76	0.78	0.83
V17	0.29	0.24	0.51
V18	0.38	0.69	0.81
V19	-0.41	0.72	0.75
V20	0.39	0.29	0.36
Average	0.49	0.54	0.67

Index by Authors

9th Hull Performance & Insight Conference (HullPIC)

Tullamore/Ireland, 25-27.3.2024




Topics: ISO 19030 and beyond / sensor technology / human factors in reporting / information fusion / big data / sea trials / uncertainty analysis / hydrodynamic models / business models / CII management

Organiser: Volker Bertram (VB conferences)
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Venue: The conference will be administered in Hamburg/Germany

Format: Papers to the above topics are invited and will be selected by a selection committee.
The proceedings will be made freely available to the general public.

Deadlines:

anytime	Optional "early warning" of interest to submit paper / participate
20.11.2023	First round of abstract selection (1/3 of available slots)
17.12.2023	Second round of abstract selection (remaining slots)
05.02.2024	Payment due for authors
15.02.2024	Final papers due

Admin. Fees: **800 €** – early registration (by 05.02.2024)
900 € – late registration

Fees are subject to German VAT

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