5th Hull Performance & Insight Conference

HullPIC'20

Hamburg, 26-28 October 2020

Edited by Volker Bertram

Sponsored by

www.jotun.com

www.insatech.com www.vaf.nl tutech.de

www.deeptrekker.com www.enamor.pl www.skysails.com

www.miros.no www.hempel.com www.selektope.com

www.hullwiper.co www.ppgpmc.com www.kyma.no www.napa.fi www.nortekgroup.com

www.akzonobel.com www.c-leanship.com www.veinland.net

www.stormgeo.com www.hoppe-marine.com www.coach-solutions.dk www.wartsila.com

www.ascenz.com www.vpsolutions.dk www.metis.tech www.idealship.de

www.ecosubsea.com greensteam.com www.stratumfive.com Shipshave.no Group-ib.com

www.fleetcleaner.com www.insilico.hr www.hasytec.com

Index

Fairy Tales Revisited – Energy Efficiency Options

Volker Bertram, DNV GL, Hamburg/Germany, volker.bertram@dnvgl.com

Abstract

The paper surveys key energy efficiency options in refit and operation of ships. A critical view is taken an advertised or published energy efficiency savings, looking into explanations for the frequent over-estimation of energy savings. Reasons for overestimation lie in nonrepresentative best cases being reported, comparisons made to particularly bad alternatives, improper correction for scaling errors in model tests, and tuning options for one operational point (design or contract point). Much could be gained by giving energy saving ranges based on long-term performance monitoring.

1. Introduction

Increasing fuel prices in the wake of the 2020 global sulphur cap and IMO's 2030 agenda with its ambitious greenhouse gas reduction targets, http://www.imo.org/en/MediaCentre/HotTopics/Documents/IMO%20SDG%20Brochure.pdf, have put the limelight on fuel efficiency in our industry. While new designs offer much larger potential gains in energy efficiency, assorted refit and operational measures may increase fuel efficiency for the fleet in service. With a deeply engrained mistrust to vendors, one might resort to "neutral" information on potential savings of such measures, e.g. IMO's GHG studies, *Buhaug et al. (2009), Smith et al. (2015)*, IMO's Global Maritime Energy Efficiency Partnership website https://glomeep.imo.org/, or OCIMF expert panel assessment for large tankers, *OCIMF (2011).*

However, even then, there is predominantly feedback of soberingly low savings in industry practice and disappointment on the side of ship owners. One of the reasons is that IMO studies are compilations coming from small groups, where typically an individual takes the lead in drafting a text, and then a handful of active group members add small modifications. As a rule, the involved members have no first-hand experience on the specific energy efficiency measures assessed and data come from internet searches, selected publications and "expert interviews" (reminiscent on occasion of the blind leading the blind).

In addition, "it's complicated" is often the best answer; energy savings may depend on many factors, such as speed, hull geometry, interaction with other energy saving measures, sea state, ship size, etc. But "it's complicated" is not very useful when we are trying to assess an investment in Excel. The next chapter will expand on the difficulties of getting good estimates for energy saving measures, albeit limited to hydrodynamic measures that may be applied to ships in service, building on *Bertram (2011,2014a)*.

2. Frequent & occasional errors in saving estimates

The relative importance of energy efficiency measures depends on many factors, in particular on ship type. For example, trim optimization is more attractive than hull maintenance for container ships, Fig.1, *Köpke and Sames (2011)*. But for large tankers, *OCIMF (2011)* rates the fuel saving potential of hull maintenance (listed as CBM = condition-based maintenance) higher than trim optimization (listed as trim assistant), namely 2.0% versus 0.3%. Sometimes the saving potential of a considered option even depends on individual ship hull and propeller characteristics, giving large scatter in reported savings even for same ship type. Modern computer simulations offer substantial progress in assessing saving potential of many devices, allowing case-by-case assessment. For example, CFD (computational fluid dynamics) allows not only quantifying the effect between ship with and without propulsion improving device, it also gives insight into flow details which explain why devices are effective in one case and counterproductive in another, Fig.2, *Zorn et al. (2010), Brehm et al. (2014)*.

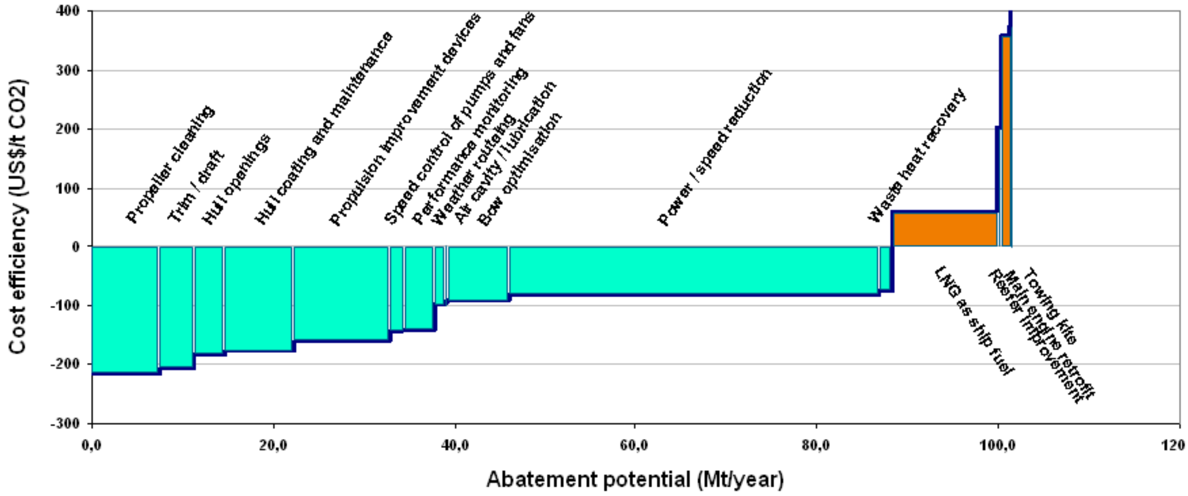


Fig.1: Marginal abatement cost curve for container vessel fleet, *Köpke and Sames (2011)*

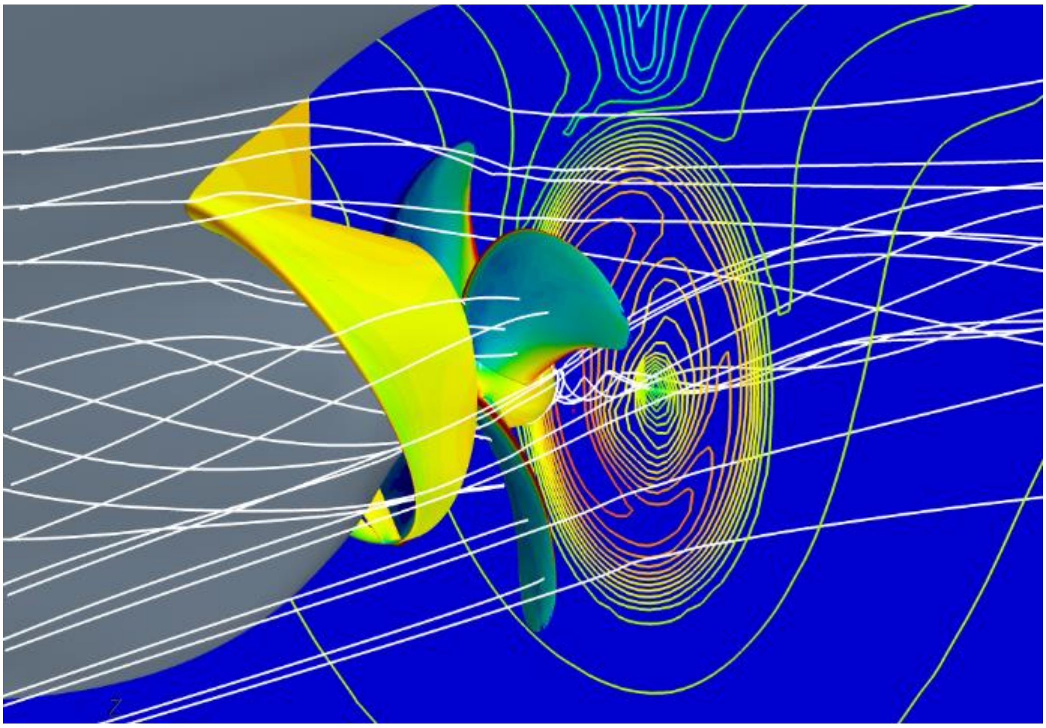


Fig.2: Full-scale CFD analysis for energy saving device, *Zorn et al. (2010)*

Many publications give unrealistically optimistic potential for fuel savings. There are various reasons for this, discussed in the following.

2.1. Good case is extrapolated as representative / average

The published savings are often for a particularly good case. This above-average case is then presented or perceived as representative "average" for other applications. As failures are far less published than success stories, making a literature survey will lead to over-optimistic numbers, especially if popular literature and websites (both containing information straight from marketing departments) are included as sources of information.

2.2. The truth is a distribution, but that is too much information

This is best illustrated in a concrete example: DNV GL Maritime Advisory Services collected achieved improvements in hull optimization projects in 2012, Fig.3.

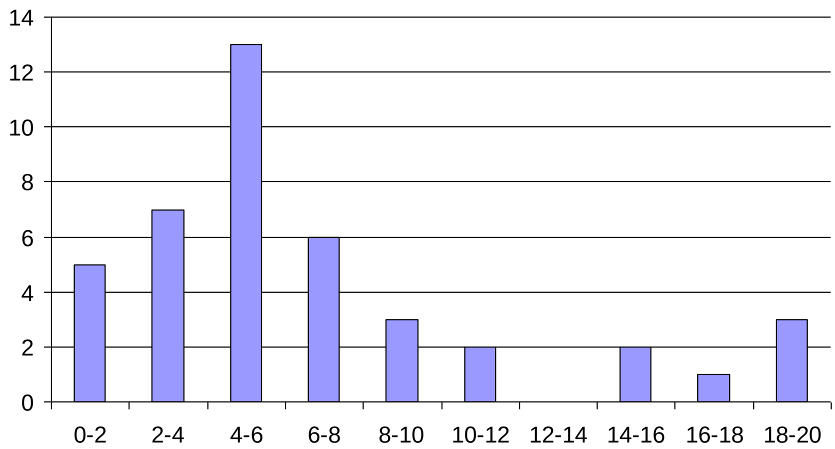


Fig.3: Gains in hull optimization projects, *Hochkirch and Bertram (2012)*

The statistical distribution may be described in various ways:

- Hull optimization may improve the fuel efficiency of a ship by up to 20%.
- Hull optimization improves the fuel efficiency of a ship by 7% on average.
- Hull optimization improves the fuel efficiency of a ship in most projects (= typically) by 4-6%.

All statements are correct. Generally, companies do not publish statistical distributions of savings achieved by their products. Instead, marketing strategies promote "up to" numbers which invariably lead to unrealistic expectations. "Up to X%" is often quoted (or entered in an overview table) as "X%" in subsequent reports or surveys.

There is also an inherent bias in the above statistics, as the most likely candidates for a hull optimization are suboptimal designs.

2.3. Rig the comparison

The secret to great energy efficiency gains is starting with a bad baseline. "After re-coating the ship with product XYZ 2000, the ship showed savings in sea trials of 8%." We can safely assume that the ship was previously coated with some of the worst paint on the market.

"After re-fitting the ship with magic nozzle XYZ, the ship showed savings in sea trials of 8%." We can safely assume that the aftbody of the ship was poorly designed with a particularly bad wake.

Publishing only the best case is a popular marketing ploy. The average reader will subconsciously interpret the published savings as representative, especially if there are no other sources of information.

2.4. Extrapolation across ship types

Often, energy saving figures may be reasonable for one ship type (say bulk carriers), but are then taken also for other ship types (say containerships), e.g. to predict the potential savings worldwide or in a region like the Baltic Sea. As ship types differ in typical resistance composition and operational procedures, such generalizations are dangerous.

2.5. Extrapolation across operational profile

Numbers are taken often for a single operational point, e.g. design draft and design speed. Energy saving devices tuned or optimized for this condition, perform much worse in off-design conditions where they may even increase fuel consumption. The focus on just one design condition is misleading at best and counter-productive at worst.

Utilization of a fuel saving device is often incorrectly assumed to be 100% of the time at sea for a ship and 100% over fleets for global estimates. Operational constraints and human factors lead e.g. for advisory software solutions often to lower utilization rates and subsequently lower savings.

2.6. Give percentage gains on a subset of total fuel consumption

The smaller the reference, the larger the savings. "Savings of X% were achieved" are easily interpreted as "You will reduce you yearly fuel bill by X%". But that is only true if the percentage is based on yearly fuel consumption. E.g. saving potential may be given for calm-water resistance, excluding added resistance in service due to fouling, sea state, wind, manoeuvring, etc. and excluding on-board energy consumption (hotel load).

2.7. Taking credit for others' achievements (muddled energy accounting)

For propulsion improving devices, published savings are often based on a comparison of power requirements measured before and after conversion. Sometimes, measurements are not corrected for hull and propeller roughness, while ship and propeller were cleaned during the refit, etc. If measured values are corrected for a "neutral condition", the correction procedure may have an uncertainty of 2-3%. Often, the claimed savings then lie within the zone of uncertainty of the assessment.

2.8. Scaling errors taking model tests at face value

Saving potential is often quoted based on model tests with questionable extrapolation to full scale. Model tests violate so-called Reynolds similarity; in laymen terms, they get everything wrong that is related to friction. Hence boundary layers and flows at appendages in the boundary layer are not similar; X% in model tests does not means X% for the real ship.

Model tests often claim an accuracy of 2%. This is misleading. Professional model basins have a repeatability of 2%, i.e. if you run the same model again and again (on different days) you may get variations of less than 2%. If we mistake that for accuracy, we would have to give an unbeatable 0% to CFD: Running the same case the next day gave exactly the same results… But if we look at extrapolated predictions to full-scale ships, we may see variations of 10% for the same geometry and same speed (Jacob Buus Petersen in personal communication some years ago). And this is for ships without energy-saving devices. With such appendages, the uncertainty will get larger.

3. Some post-heretic thoughts

Of course, it is fun to bash colleagues who promote energy savings evoking too high hopes. I had my fun. What do we do now? Here are some thoughts:

- We should give energy savings based on yearly consumption of a typical ship with a typical profile, e.g. a 8000 TEU containership or a 200000 tdw tanker. We can still give payback times in addition, e.g. for cheap measures that have great payback time, even if they save only small percentages of the overall fuel bill. But the "standard" ship and profile gives some comparability that is now lacking.
- We should give ranges for savings, with min and max and average, maybe also typical, values. *OCIMF (2011)* and https://glomeep.imo.org/ may serve as role models.
- We shouldn't give model-basin results for hydrodynamic energy saving devices. Either use professional CFD or (even better) performance monitoring.
- We should make very clear if a saving is given only for design condition. If so, at least a qualitative discussion of expected performance in off-design condition should be given.
- When making global fleet-wide predictions, we should consider a large percentage of the world's fleet that will not adopt or not benefit from a measure. Correspondingly, predicted

global savings of CO_2 or other emissions should be corrected, e.g. 5-10% of the world fleet may adopt this measure within the next 20 years, hence the global CO_2 savings would be … in 10 years and … in 20 years.

- Doing nothing is often the worst strategy. Even if claims for fuel savings are optimistic/exaggerated, the measure in itself may still make sense. Start with reasonable payback times for energy efficiency measures. Is it reasonable to expect you get your money back within 1 year and then a constant stream of "money for nothing" will come in?
- Make performance-based contracts – not "I pay if you reach a threshold", but "I pay 1% for each 2% you save me". That concerns owner-charterer contracts, paint supplier-owner contracts, or any other contract in the industry. If I get rewarded for better performance, I am more motivated to deliver good performance.

Ship hydrodynamics are complicated, but the basics are not rocket science. Understand the basics and contact experts of your choice for the finer points. With a bit of understanding, you can avoid major pitfalls and resulting disappointment.

4. My take on some energy saving options

The following has some of my very personal opinions; I have no idea whether they are in line with my company's official views. If they are clever and profound, they are. Otherwise, they are my private opinion.

- Propeller cleaning
  Propeller roughness increases in time due to cavitation, impingement, calcareous deposits and fouling. Rather than following fixed intervals, propeller cleaning strategies should be condition-based (using underwater inspections, possibly by robots, or performance monitoring).

- Trim optimization
  General rules of thumb (e.g. "always 1 foot to stern") are fairy tales, *Bertram (2014b)*. Trim optimization software based on "numerical sea trials" (viscous CFD simulation of ship with propeller at full-scale Reynolds numbers) is my recommended approach, e.g. *Hochkirch and Mallol (2013)*. For many ship types, this may lead to 1-2% reduction in yearly overall fuel consumption. (Publications and websites advocating this approach and associated products will give higher percentage, but these are then based on calm-water resistance.) Payback depends on ship engine power, number of sister vessels in a fleet and fuel price; use a simple excel spreadsheet payback calculation. If trim optimization is used, re-use the available power-speed(-and more) matrix for performance monitoring, *Bertram (2013)*.

- Performance monitoring
  Monitoring as such does not save any fuel, but creates transparency. Transparency between business partners (such as coating supplier and ship owner) can enable better contracts based on performance, unlocking currently dormant energy saving potential. I believe this potential may reach 5-10% for hull management, but have no reference to support this claim. Transparency also is likely to change crew behaviour, leading to better fuel efficiency, *Köpke and Catarino (2012)*.

- Propulsion Improvement Devices (PIDs) a.k.a. Energy Saving Devices (ESDs)
  Opinions on PIDs scatter widely, from negative effects (increasing fuel consumption) to more than 10% improvements. The truth is the time-honoured "it depends". Wake-equalizing ducts are generally not suitable for slender ships, as these have already more homogeneous wakes than full ships (such bulkers and tankers). The effectiveness of PIDs should be assessed on an individual case base, using full-scale CFD simulations, *Hochkirch and Mallol (2013)*. Assessment based on performance monitoring often is problematic as during refits assorted other measures improve performance (cleaning, other retrofits) making it difficult to single out the

effect of the PID retrofit. PIDs generally lose effectiveness in off-design conditions, e.g. slower speeds. Also, published savings generally refer to calm-water conditions and smooth hulls. In years to come, we will have a better assessment of individual devices, due to better and more widely used CFD and occasional performance monitoring insight, such as *Themelis et al. (2019).*

- Air lubrication
  The basic idea is that a layer of air (on part of the hull) reduces the frictional resistance. In principle, the technology is most attractive for large, slow ships with small draft. For a converted chemical tanker, *Silberschmidt et al. (2016),* report 5% net savings in yearly fuel consumption for propulsion, demonstrated in third-party evaluation. I hope we will see similar evaluations for cruise ships and ferries, adopting air lubrication. It is encouraging to see that the technology vendor Silverstream Technologies pushes for such performance monitoring evaluation, *De Freitas et al. (2019),* also via an IMO working group.

- Wind-assistance
  With expected lower operational speeds, the case for wind assistance becomes more attractive. There is no shortage of proposals for wind-assistance technologies (Flettner rotors, fixed sails, soft sails, kites, etc.), but the technologies are offered mainly by small start-up companies, struggling with business issues such as funding for R&D and worldwide sales and customer support. Savings from harnessing wind power depend strongly on operational profiles and regions of operation. This makes general claims or predictions for global fleets questionable. Even for a given ship and rather sophisticated engineering prediction models, the strong non-linearities involved in wind assistance introduce an unavoidable large uncertainty. In an industry that likes to play it safe, this is a handicap.

- Speed reduction (slow steaming)
  Speed reduction is the most effective way to improve fuel efficiency. A 10% lower design speed saves roughly 30% in calm-water required power. However, added resistance in waves and wind will gain in importance. Thus, the so-called "sea margin" should be increased, reducing the savings in installed power to maybe 25% (which still is a significant saving!). For global fuel and emission savings, the reduced yearly delivery capacity has to be considered as well. Taking port time and capacity utilization into consideration, we may estimate 5% lower yearly delivery capacity which needs to be compensated for (ideally by larger ship size). The 25% reduction in installed power is very attractive for the EEDI, https://www.marpol-annex-vi.com/eedi-seemp/. However, 25% savings in EEDI do not translate into 25% savings in fuel consumption. The ship will have a spectrum of used power. The maximum is rarely used. If the installed power is reduced, the ship will use the same operational speed and power whenever possible. In regions of lower power demand (partial loading and/or lower speeds), the smaller engine can still supply enough power and will just operate at higher MCR (maximum continuous rating) than a bigger engine. The fuel consumption is probably a bit lower, as higher MCR will typically mean being closer to optimum SFOC (specific fuel oil consumption), but fuel savings for same draft and speed will be closer to zero than to 25%. Only in cases where the maximum power is reached, the speed will be forced to be lower than for a ship with a bigger engine. Thus, lower design speed does not translate into consistently lower operational speed and fuel consumption. For a containership with a 68 MW engine installed, the time distribution of engine load (June 2019) was monitored and plotted, Fig.4. In this case, there was never a load in excess of 65%. A 25% lower engine power would then always suffice. For a bulk carrier with a 13.5 MW engine installed, Fig.5 shows the corresponding time distribution of engine load. Here, in 2.9% of the time 75% MCR were exceeded. If you allow occasional 5% overload, it would be only 1.4% of the time where an engine with 25% lower engine power imposes a (slightly) lower speed. For given design in slow steaming, hull, propeller and engine operate in off-design conditions and thus at a lower efficiency. Often refit measures for hull (bow refit), propeller and machinery (e.g. de-rating) are then advisable.

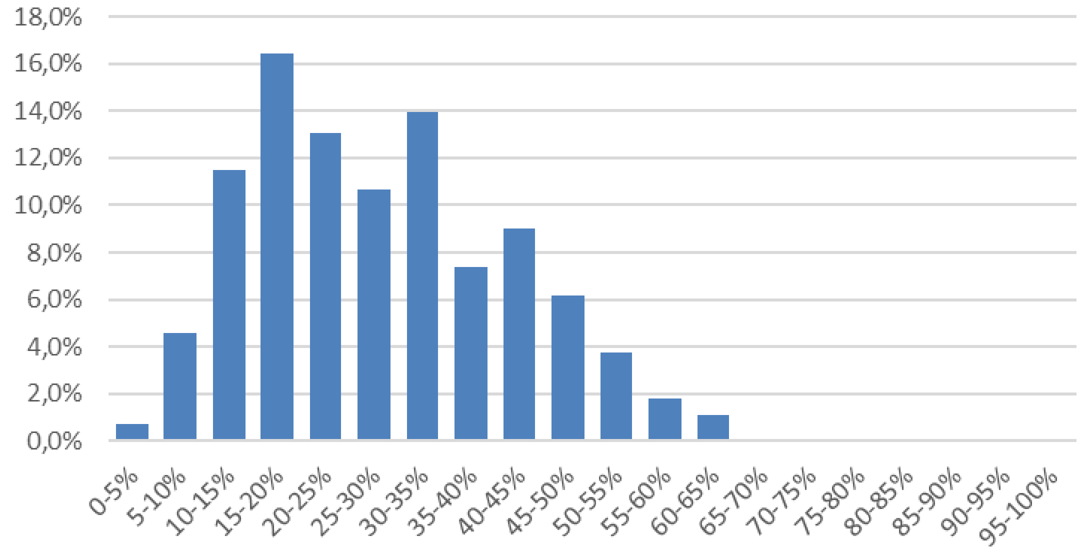


Fig.4: Distribution of MCR load profile for 68 MW engine

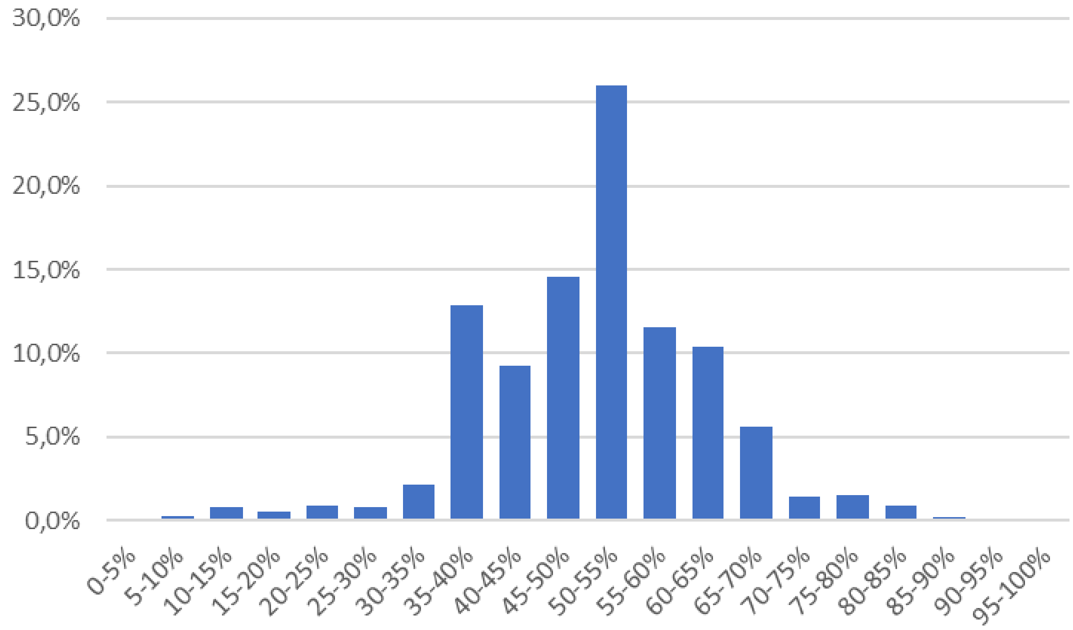


Fig.5: Distribution of MCR load profile for 13.5 MW engine

5. Conclusions

Most numbers for energy saving potential in ship operation are too high, due to deliberately or unintentionally misleading phrasing or extrapolation errors. Having a common reference case for in-service power, e.g. for a containership and a tanker, and giving a bandwidth of typical savings would be a good start to get closer to more realistic predictions.

We should use fuel saving figures based on performance monitoring rather than marketing promises and spot-check values from model tests or sea trials for a singular speed-draft-trim combination in calm water.

Consistently over-optimistic predictions will lead to mistrust and ultimately also to an unfortunate reluctance to adopt fuel saving measures where they could benefit. For some measures, there is unavoidable uncertainty. Wind assistance is a prime example. Here, I believe that it is better to be honest and make the uncertainty transparent to potential customers.

In view of frequent over-optimistic estimates, we should reconsider our efforts to reach IMO's 2030 and 2050 goals for CO_2 emissions from the world's fleet. We should do more and for more ships – if we are serious about reaching our goals.

References

BERTRAM, V. (2011), *Fuel efficiency options – Gold mines and mine fields*, 33rd Motorship Propulsion & Emission Conf., Copenhagen

BERTRAM, V. (2013), *Trim Optimization Meets Hull Performance*, Lloyds List Seminar "Hull Management and Performance", London

BERTRAM, V. (2014a), *Promises, promises – Critical assessment of measures to improve energy efficiency in containerships*, RINA Conf. Design & Operation of Container Ships, London

BERTRAM, V. (2014b), *Trim Optimisation – Don't blind me with science!*, The Naval Architect, September, p.66-68

BREHM, A.; BERTRAM, V.; ZORN, T. (2014), *Full-scale CFD analyses for energy saving devices in DNV GL Maritime Advisory practice*, Jahrbuch der Schiffbautechnischen Gesellschaft, Springer

BUHAUG, Ø.; CORBETT, J.J.; ENDRESEN, Ø.; EYRING, V.; FABER, J.; HANAYAMA, S.; LEE, D.S.; LEE, D.; LINDSTAD, H.; MARKOWSKA, A.Z.; MJELDE, A.; NELISSEN, D.; NILSEN, J.; PÅLSSON, C.; WINEBRAKE, J.J.; WU, W.Q.; YOSHIDA, K. (2009), *Second IMO GHG study 2009*, International Maritime Organization (IMO), London, http://www.imo.org/en/OurWork/Environment/PollutionPrevention/AirPollution/Documents/SecondIMOGHGStudy2009.pdf

HOCHKIRCH, K.; BERTRAM (2012), *Ship hull optimization – Past, present, future*, Hansa 149/9

HOCHKIRCH, K.; MALLOL, B. (2013), *On the importance of full-scale CFD simulations for ships*, 12th COMPIT Conf., Cortona, pp.85-95, http://data.hiper-conf.info/compit2013_cortona.pdf

KÖPKE, M.; CATARINO, J. (2012), *Fuel oil consumption reduction through awareness during ship Operation*, 9th Green Ship Technology Conf., Copenhagen

KÖPKE, M.; SAMES, P. (2011), *Outlook on CO_2 emissions of the container world fleet and possible reduction targets*, 8th Green Ship Technology Conf., Oslo, http://docplayer.net/33153658-St-2011-the-8th-annual-green-ship-technology-conference.html

OCIMF (2011), *GHG emission-mitigating measures for oil tankers – Part A: Review of reduction potential*, Oil Companies International Marine Forum, London, https://www.ocimf.org/media/8922/GHG%20Emission-Mitigating%20Measures%20for%20Oil%20Tankers%20Part%20A%20Review%20of%20Reduction%20Potential%20FINAL.pdf

SILBERSCHMIDT, N.; TASKER, D.; PAPPAS, T.; JOHANNESSON, J. (2016), *Silverstream® System – Air Lubrication Performance Verification and Design Development*, 10th Symp. High-Performance Marine Vehicles (HIPER), Cortona, pp.236-246, http://data.hiper-conf.info/Hiper2016_Cortona.pdf

SMITH, T.W.P.; JALKANEN, J.P.; ANDERSON, B.A.; CORBETT, J.J.; FABER, J.; HANAYAMA, S.; O'KEEFFE, E.; PARKER, S.; JOHANSSON, L.; ALDOUS, L.; RAUCCI, C.; TRAUT, M.; ETTINGER, S.; NELISSEN, D.; LEE, D.S.; NG, S.; AGRAWAL, A.; WINEBRAKE, J.J.; HOEN, M.;

CHESWORTH, S.; PANDEY, A. (2015), *Third IMO GHG study 2014*, International Maritime Organization (IMO), London, http://www.imo.org/en/OurWork/Environment/PollutionPrevention/AirPollution/Documents/Third%20Greenhouse%20Gas%20Study/GHG3%20Executive%20Summary%20and%20Report.pdf

THEMELIS N.; SPANDONIDIS, C.; CHRISTOS GIORDAMLIS, C. (2019), *Evaluating the Efficiency of an Energy-Saving Device by Performance Monitoring*, 4th HullPIC Conf., Gubbio, pp.56-64, http://data.hullpic.info/HullPIC2019_gubbio.pdf

ZORN, T.; HEIMANN, J.; BERTRAM, V. (2010), *CFD Analysis of a Duct's Effectiveness for Model Scale and Full Scale*, 13th Numerical Towing Tank Symp. (NuTTS), Duisburg, http://www.uni-due.de/imperia/md/content/ist/nutts_01_2010_duisburg.pdf

CFD for Performance Monitoring – Current Capabilities and Limits

Volker Bertram, DNV GL, Hamburg/Germany, volker.bertram@dnvgl.com

Abstract

This paper gives an introduction to flow simulations with relevance to hull performance monitoring: resistance & propulsion simulations, seakeeping, rudder forces and wind forces. The paper describes general approaches, applications where we have confidence in CFD simulations and those where current applications reach their limits.

1. Introduction to numerical fluid dynamics

Numerical ship hydrodynamics denotes techniques to solve equations describing the physics of flows, *Bertram and Couser (2007), Bertram (2012)*. The most important techniques for us are:

- Potential-flow computations – Potential-flow codes do not model viscosity (and associated effects like the boundary layer). They also do not model breaking waves. On the other hand, they are fast and relatively easy to handle. They are widely used for seakeeping computations.
- CFD (Computational Fluid Dynamics) – Codes (usually based on the Reynolds Averaged Navier Stokes Equations = RANSE) model viscosity directly in the field equations. All modern CFD codes are able to capture breaking waves. All major commercial codes and the open-source alternative OpenFOAM are verified in terms of numerical implementation, and their application is validated for many marine applications.

Despite the growing complexity and level of detail in flow simulations, CFD projects today are often noticeably shorter than they were two decades ago, *Peric and Bertram (2011)*. This is due to more user-friendly software and parallel processing. Computations with systematic parameter variations are today performed within integrated environments, such as CAESES, www.caeses.com. The integrated design environment combines hull description using parametric modelling, interfaces to most modern flow solvers, several optimization algorithms, and software to handle process management and user interface. *Gatin et al. (2019)* present an application for largely automatic, systematic CFD simulations resulting in power curve prediction; such a solution can be used for trim optimization, but also for performance monitoring corrections. Re-using CFD-based knowledge bases for trim optimization and performance monitoring makes a better business case.

Another key aspect has led to flow simulations becoming the widely accepted and sometimes preferred tool that it is today, namely validation and the resulting trust. Since 1980, dedicated workshops for the validation of marine CFD simulations have been held, now following a 5-year rhythm. The most recent one was the Tokyo Workshop on CFD in Ship Hydrodynamics in 2015, http://www.t2015.nmri.go.jp/. The high quality of the experimental data and the detailed comparison, e.g. Fig.1, has created confidence in CFD particularly for resistance & propulsion applications. However, the validation workshops document best-practice results. As CFD is much more affordable and accessible than model basins, we see a much larger variation in quality in practice.

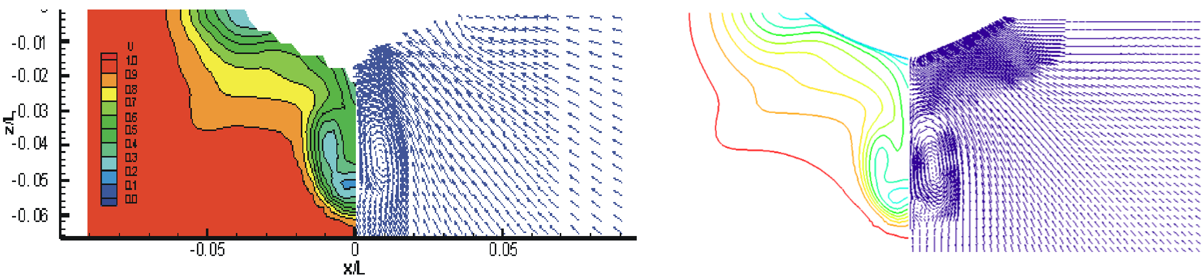


Fig.1: Measured (left) and computed (right) wake field of a tanker, *Peric and Bertram (2011)*

2. Applications

2.1. Resistance & propulsion

For performance monitoring, we are primarily interested in expressing ideal (= for smooth ships) power as function of draft, trim, and speed. Important points in this respect are:

- Wave making and wave breaking
  For design condition, the wave making is generally minimized (often using potential-flow wave resistance codes and model tests). For performance monitoring, we also need to look at off-design conditions which are not covered by classical model tests. For these conditions, breaking waves are important, Fig.2, and thus CFD tools should be employed ("free-surface RANSE" simulations in the jargon of CFD experts), *Krapp and Bertram (2016)*.

Fig.2: Off-design draft and speed leads often to massive wave-breaking

- Model scale or full scale
  Model tests violate some similarity laws, *Bertram (2012)*. Notably wave-breaking and boundary layers are different from the full-scale ship, *Hochkirch and Mallol (2013)*. Thus, CFD computations should be performed at full scale ("numerical sea trials"). Unfortunately, many CFD simulations in practice are performed at model-scale conditions, as customers like to use model tests to check the CFD simulations. With growing understanding of CFD, we should see a change in this practice and a move towards full-scale simulations.

- Geometry simplifications
  Hull details such as welds are not captured by CFD models for power prediction. Variations in welds can account for significantly higher resistance. For a tanker, *Ciortan and Bertram (2014)* give 2% for poor welds. Such welds also generate higher turbulence intensity than generally assumed in CFD computations, Fig.3.

  Often the propeller is not geometrically modelled, Fig.4; instead the main effects of the propeller are included via so-called body-forces. These are externally specified forces to mimic thrust and swirl of the propeller. For performance monitoring purposes, this modelling approach is fine. Only directly at the propeller, this simplified approach introduces unacceptable changes in the simulated flow.

  Krapp et al. (2016) report 5.6% variations in measured power in sea trials for 7 sister vessels. It is anybody's guess how much of these variations are due to differences in the as-built hulls and how much due to variations in the measuring process. However, unless detailed scans of the as-built hull are used to generate the CFD model, such variations will always have to be expected. CFD predictions (like model tests) can never be more accurate than these variations.

Microscopic or even changes in the order of mm are not captured geometrically in CFD models. The roughness of surfaces can be varied in CFD computations, e.g. *Eca et al. (2010), Demirel et al. (2014), Östman et al. (2017,2019), Vargas and Shan (2017), Vargas et al. (2019)*. There is no consensus among CFD experts how reliable such parameter studies are, but the qualitative changes appear plausible. Changing roughness parameters locally over the ship may yield valuable insight into the location-dependent effect of fouling, supporting better hull maintenance strategies, *Vargas et al. (2019)*.

Our theoretical knowledge on roughness and boundary layers stems from ideal laboratory conditions, mostly for flat plats. Sea water with many impurities flowing over ship hulls with roughness levels in the mm order of magnitudes (with welds and fouling) may behave differently, but I am not aware of any investigation proving such differences.

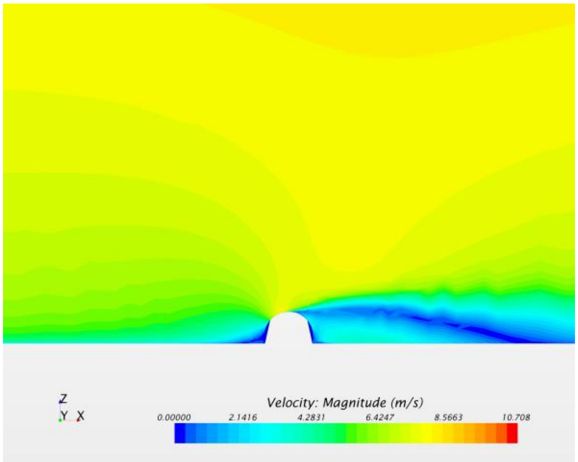


Fig.3: Welds lead to higher frictional resistance, but are generally not captured in global CFD models.

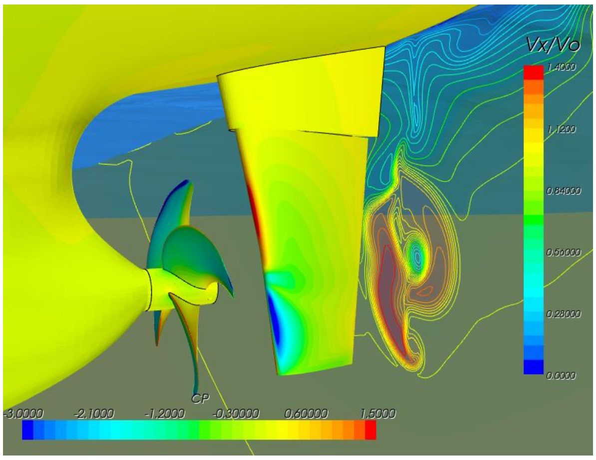


Fig.4: RANSE simulations capture the key features of the flow (breaking waves, boundary layer) and the key features of the ship (hull, propeller, rudder).

- <u>Flow simplifications</u>
  Model tests assume laminar-turbulent flow transition at a given distance from the leading edge. As this distance does not scale properly, model tests enforce the transition by turbulence stimulators (sand strips or studs). In CFD, generally fully turbulent flow is assumed from the very beginning, although some researchers have used “numerical sand strips”. I believe that the standard approach with fully turbulent flow from the beginning reflects the conditions in full scale and realistic ocean environment better than the model tests. Waves and ship motions change the flow and should create fully turbulent flow essentially from the beginning.

  CFD computations use simplified turbulence models. Up until the 1990s, turbulence modelling was the usual suspect to be blamed for unsatisfactory results. Since then, turbulence modelling has progressed significantly. The propeller behind the ship dominates the flow and makes discussions over the turbulence model rather academic for performance monitoring.

Take-home messages:

- Properly performed CFD simulations are by now at least as accurate as model tests for full-scale predictions.
- Neither model tests nor CFD can account for as-built variations in sister vessels.

- For parameter variations (such as trim, draft and speed for a given hull), CFD is superior due to parallel processing and easier automation of analyses, e.g. *Gatin et al. (2019)*.
- CFD simulations for trim optimization tools should be reused for performance monitoring. If properly planned, this re-use of hydrodynamic information can lead to much better economics.
- CFD may support better hull maintenance strategies, such as deciding where to clean better or where to use more expensive coatings.

2.2. Seakeeping

There is a confusing multitude of computational methods for seakeeping with assorted strengths and shortcomings, *Bertram (2012), Bertram and Couser (2014)*. Primarily, performance monitoring needs added power in small to moderate seaways. Here, linear analyses based on potential-flow theory are recommended as best overall approach, Fig.5. These analyses are relatively fast, allowing the investigation of many parameters (wave length, wave direction, ship speed, draft, etc.). More complicated CFD methods usually do not give better results for added resistance in waves, due to a combination of grid-resolution issues and problems with subtracting the calm-water resistance, *Söding et al. (2012b), Bertram et al. (2016)*. For waves shorter than half the ship length, virtually all approaches fail to predict added resistance properly, *Bertram (2016)*. Notable exceptions are:

- MARIN's FATIMA code, *Dallinga et al. (2011)*, a frequency-domain conversion of the time-domain code developed by *Bunnik (1999)*
- DNV GL's RANKINE code, *Shigunov and Bertram (2014)*, mostly developed by *Söding et al. (2012a,c)*.

Popular strip methods are not appropriate for capturing added resistance, especially for tankers and bulkers, and for oblique waves. Published results showing good agreement with experiments are misleading as nonrepresentative best cases are shown (head waves, wave length between 0.5 and 2 times ship length).

While computing added resistance is already difficult, it is not enough. The effects of seaway on propeller efficiency and indirect resistance parts due to compensation of drift forces should be included. I believe FATIMA and RANKINE can do the job. However, there is little sense in going to the required expense (think 5-digit Euro numbers if you want to cover the variations of parameters needed) as long as we use crude estimates for the seaway.

Maybe, in years to come, we will see simple formulas adapted to certain ship types which share certain similarities (e.g. tankers or container ships). Meta-models, based on numerical analyses of a series of ship designs with parameter variation, as proposed by *Couser et al. (2011)*, could yield reasonably accurate predictions virtually instantaneously.

More recently, the performance monitoring community has discussed using shipboard sensors to derive ship resistance. I believe the point was raised by Michael vom Baur in discussion at the 1st HullPIC conference. The general idea seems to be as follows:

1. Sensors measure accelerations in 6 degrees of freedom (within linear ship seakeeping theory then also motions in 6 degrees of freedom are known).
2. By reverse engineering, the seaway causing these motion histories is derived (best-fit approximation)
3. For given seaway, the added resistance and power is then determined.

For the second step, a simpler computational method, e.g. a strip method might be used; motions and accelerations can be determined by an order of magnitude more accurately than added resistance. Then the problems of accurate determination of added resistance/power in waves apply again. However, using motion sensors on board, we could come to a much better estimate of the ambient seaway than currently by crew estimates or coarse hindcast MetOcean data.

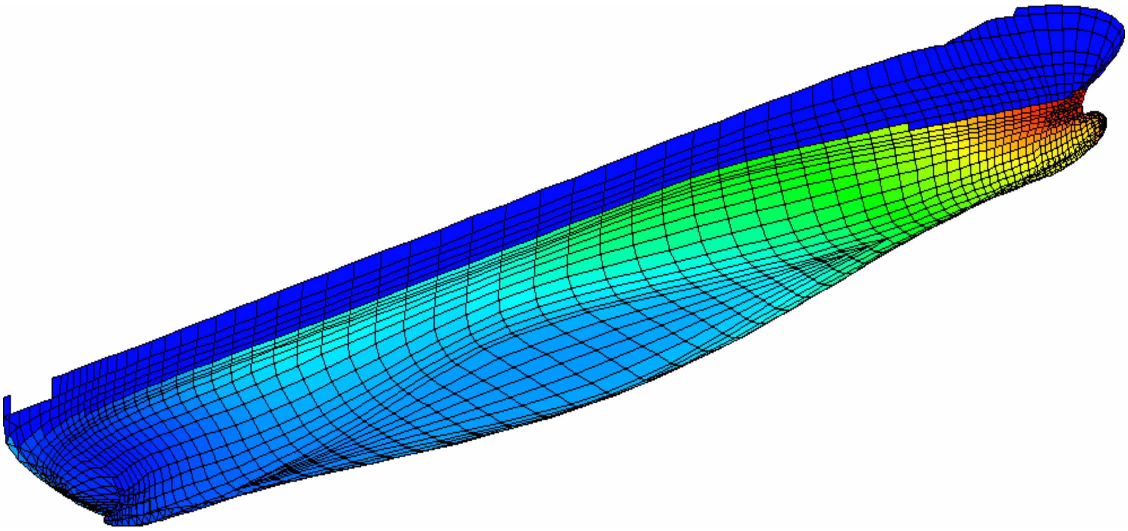


Fig.5: Seakeeping grid for containership

2.3. Maneuvering and rudder flows

Rudder forces for rudders at small-to-moderate angles can be computed by semi-empirical methods, *Söding (1998)*. CFD can be used for rudder flows, especially for larger angles with massive flow separation or cavitation, *El Moctar (2007), Brehm et al. (2011),* but are unnecessary overkill for performance monitoring. In normal ship operation at higher speeds, rudder angles are small.

Most maneuvering models (as in nautical simulators or in simple estimates, see e.g. the appendix of *Bertram (2017)*) use force coefficients to express forces and moments which in turn can be used in simulating maneuvers. The approach is very fast, allowing real-time response. However, the determination of the force coefficients requires extensive (and expensive) model testing or CFD. The trend is towards using CFD, Fig.6. However, for performance monitoring, the budget constraints and the low importance of maneuvering hydrodynamics mean that we will at best use published force coefficients for a "similar" ship for rough estimates.

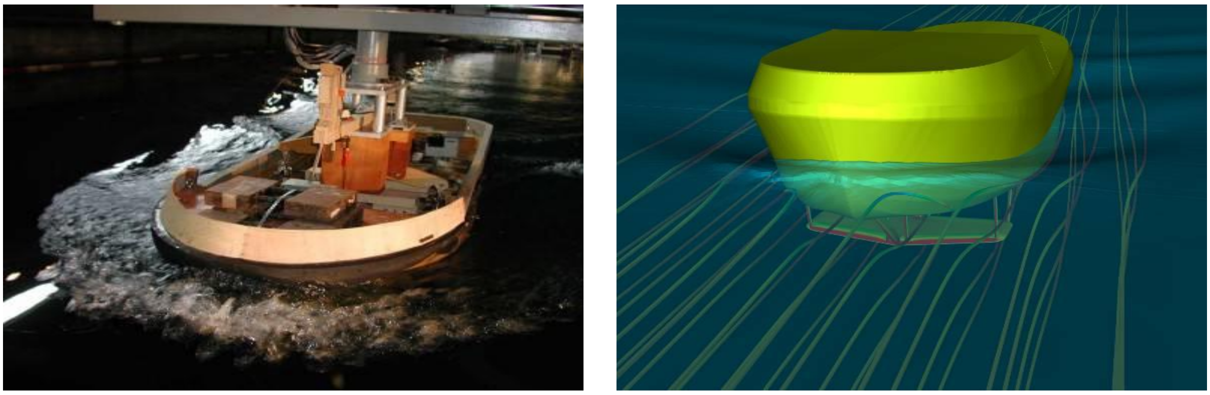


Fig.6: Model tests to determine hydrodynamic coefficients (left) are now replaced by virtual experiments using CFD (right), source: Voith Hydro

2.4. Aerodynamics

Although wind tunnel tests are still widely used, CFD has evolved as an alternative comparable in accuracy, level of detail, time requirements and cost, Fig.7, *Schmode and Bertram (2002), El Moctar and Bertram (2002)*. For larger parameter studies (considering not just variation of wind direction, but also draft), CFD would be the preferred choice due to easy parallel computing. Such parameter variations could lead to more accurate wind force models for performance monitoring. CFD might also be used to determine local flow variation at the location of wind anemometer, *Moat et al. (2005)*, to compensate for local flow distortion due to the deckhouse and the other equipment. Alas, a lot could be done, and little is actually done in using CFD for wind forces / air resistance.

The effort is still too high to use CFD-based, tailored wind models as a standard option in performance monitoring, but for ships where aerodynamic CFD investigations are performed in any case (typically cruise vessels), this knowledge should be re-used; more precisely, parameter variations should be added to the specifications to obtain better performance models at low price.

The validity of the semi-empirical formulas used in ISO 19030 should be investigated by CFD, e.g. the assumption that the non-dimensional wind force coefficients remain (virtually) constant with draft variations for a ship, *Bertram (2017)*.

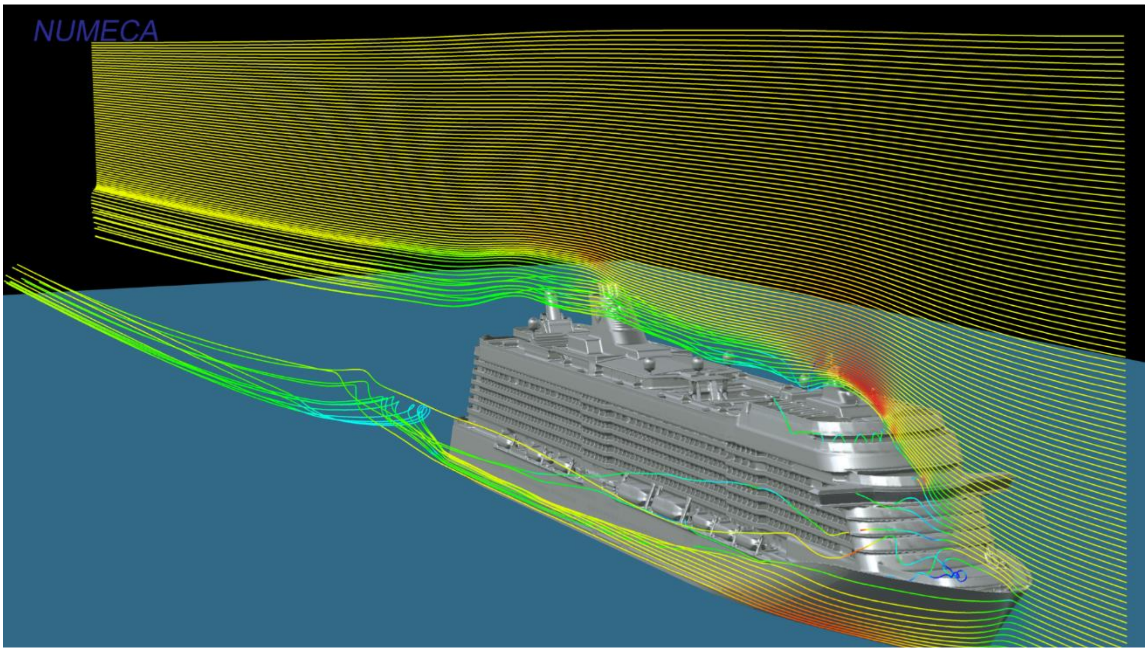


Fig.7: CFD simulations for wind forces and local flow investigations, source: Meyer Turku and FINEMarine (Numeca)

3. Requirements – What does it take to do CFD for performance monitoring?

Having discussed the applications of numerical ship hydrodynamics, let us have a brief look at the requirements for such simulations, *Bertram and Couser (2010), Bertram (2012)*:

- Software − I recommend using commercial software from large, well established vendors or tailored solutions based on OpenFOAM. Such software is extensively validated, with known scope and limits of applications. Large user groups add transparency and serve as informal help sources. Commercial software still needs customization for specific applications and efficient processes.
- Hardware - State-of-the-art computations employ parallel computing (HPC = high-performance computing). More recently, commercial software licences and parallel computing capacity can be rented "by the hour", *Hildebrandt and Reyer (2015)*. This makes HPC affordable also for small and medium-sized enterprises.
- Trained experts - Experience is needed in modelling, which is a critical phase determining largely response time, cost and quality of results. Computations should be put in the hands of CFD experts with domain knowledge (i.e. experts both in the field of application and in the

code employed) to get good results. This experience may in narrow applications (such a speed-power curves for conventional ships) be incorporated in macros, i.e. automatic routines, allowing essentially “anybody” to run the application, *Hochkirch and Hahn (2017), Gatin et al. (2019)*.

For resistance and propulsion calculations for baselines, emerging online solutions for “virtual trials” (simulation of full-scale ship with propeller in calm water) are most interesting. Here, essentially only the ship geometry, a list of speeds and drafts and trims and a credit card are needed.

The mesh generation, computation on parallel computers and reporting are performed at roughly a third of the time and costs needed for model tests, *Hochkirch and Hahn (2017)*.

4. Conclusions

CFD has matured to be a viable and sometimes superior alternative to model tests. Specific applications with relevance to performance monitoring are:

- Numerical sea trials, steady speed of ship in initially calm water with working propeller at full-scale conditions. Such simulations give reliable hydrodynamic knowledge bases for the calm-water performance of ships. They should be based on RANSE simulations (CFD) and may be ordered online by now.
- Seakeeping simulations are less important as we filter generally for moderate and higher seaways. The best options at present are 3d Rankine-source-method flow-codes offered by DNV GL and MARIN, *Bertram et al. (2016)*. Simulations only make sense if the knowledge is re-used for other applications and seaways are identified with greater accuracy.
- Maneuvering coefficients for force coefficient analyses might be based on CFD. For performance monitoring, the benefit achieved does not justify the effort involved. Instead, published force coefficients for similar ships or ship types may be taken as rough estimates.

References

BERTRAM, V. (2012), *Practical Ship Hydrodynamics,* Butterworth & Heinemann, Oxford

BERTRAM, V. (2017), *Some heretic thoughts on ISO 19030*, 2nd Hull Performance & Insight Conf. (HullPIC), Ulrichshusen, pp.5-11

BERTRAM, V.; COUSER, P. (2007*), CFD possibilities and practice*, The Naval Architect, September, pp.137-147

BERTRAM, V.; COUSER, P. (2010), *Aspects of selecting the appropriate CAD and CFD software,* 9th Int. Conf. Computer and IT Applications in the Maritime Industries (COMPIT), Gubbio, pp.20-29

BERTRAM, V.; COUSER, P. (2014), *Computational methods for seakeeping and added resistance in waves,* 13th Conf. Computer and IT Applications in Maritime Industries (COMPIT), Redworth, pp.7-16

BERTRAM, V.; ZORN, T.; ROGNEBAKKE, O. (2016), *Advanced simulations = Better results. Really?*, 19th Numerical Towing Tank Symposium (NuTTS), St Pierre d'Oléron

BREHM, A.; BERTRAM, V.; EL MOCTAR, O. (2011), *CFD guided improvement of a cavitation-prone rudder,* 14th Numerical Towing Tank Symposium (NuTTS), Poole

BUNNIK, T.H.J. (1999), *Seakeeping calculations for ships, taking into account the non-linear steady waves*, PhD Thesis, TU Delft

CIORTAN, C.; BERTRAM, V. (2014), *RANSE simulations for the effect of welds on ship resistance,* 17th Numerical Towing Tank Symp., Marstrand

COUSER, P.; HARRIES, S.; TILLIG, F. (2011), *Numerical hull series for calm water and sea-keeping,* 10th Conf. Computer and IT Applications in the Maritime Industries (COMPIT), Berlin, pp.206-220

DALLINGA, R.P.; BUNNIK, T.H.J.; MONTGOLFIER, E. de (2011), *Reducing added resistance of ships in waves,* Greenship Conf., Wuxi

DEMIREL, Y.D.; KHORASANCHI, M.; TURAN, O.; INCECIK, A.; SCHULTZ, M.P. (2014), *A CFD model for the frictional resistance prediction of antifouling coatings*, Ocean Engineering 89, pp.21–31

ECA, L.; HOEKSTRA, M.; RAVEN, H.C. (2010), *Quantifying roughness effects by ship viscous flow calculations*, 28th Symp. Naval Hydrodyn., Pasadena, pp.861-877

EL MOCTAR, O.M. (2007), *How to avoid or minimize rudder cavitation*, 10th Num. Towing Tank Symp. (NuTTS), Hamburg

EL MOCTAR, O.M.; BERTRAM, V. (2002), *Computation of viscous flow around fast ship superstructures*, 24th Symp. Naval Hydrodyn., Fukuoka, pp.938-947

GATIN, I.; VUKCEVIC, V.; JASAK, H. (2019), *Fully Automated CFD Analysis for Full-Scale Ship Hydrodynamics,* 4th Hull Performance & Insight Conf. (HullPIC), Gubbio, pp.153-161

HILDEBRANDT, T.; REYER, M. (2015), *Business and technical adaptivity in marine CFD simulations - Bridging the gap*, 14th Conf. Computer and IT Applications in the Maritime Industries (COMPIT), Ulrichshusen, pp.394-406

HOCHKIRCH, K.; HAHN, C. (2017), *Cloud-based numerical towing tanks – Anytime, anywhere and for anybody,* 11th Symp. High-Performance Marine Vehicles (HIPER), Zevenwacht, pp.66-69

HOCHKIRCH, K.; MALLOL, B. (2013), *On the importance of full-scale CFD simulations for ships,* 12th Conf. Computer and IT Applications in the Maritime Industries (COMPIT), Cortona, pp.85-95

KRAPP, A.; BERTRAM, V. (2016), *Hull performance analysis – Aspects of speed-power reference curves*, 1st Hull Performance & Insight Conf. (HullPIC), Pavone, April, pp.41-48

MOAT, B.I.; YELLAND, M.J.; MOLLAND, A.F.; PASCAL, R.W. (2005), *The effect of ship shape and anemometer location on wind speed measurements obtained from ships,* 4th Int. Conf. Marine Computational Fluid Dynamics, Southampton pp.133-139

ÖSTMAN, A.; KOUSHAN, K.; SAVIO, L. (2017), *Numerical and experimental investigation of roughness due to different type of coating,* 2nd Hull Performance & Insight Conf. (HullPIC), Ulrichshusen, pp.227-235

ÖSTMAN, A.; KOUSHAN, K.; SAVIO, L. (2019), *Numerical and experimental investigation of roughness due to different type of coating,* 4th Hull Performance & Insight Conf. (HullPIC), Gubbio, pp.153-161

PERIC, M.; BERTRAM, V. (2011), *Trends in industry applications of CFD for maritime flows,* 10th Conf. Computer and IT Applications in Maritime Industries (COMPIT), Berlin, pp.8-18

SCHMODE, D.; BERTRAM, V. (2002), *Aerodynamic flow computations for a Superfast ferry,* 3rd Int. Conf. High-Performance Marine Vehicles (HIPER), Bergen, pp.345-354

SHIGUNOV, V.; BERTRAM, V. (2014), *Prediction of added power in seaway by numerical simulation,* 9th Int. Conf. High-Performance Marine Vehicles (HIPER), Athens, pp.102-113

SÖDING, H. (1998), *Limits of potential flow theory in rudder flow predictions*, 22nd Symp. Naval Hydrodyn., Washington

SÖDING, H.; GRAEFE, A.v.; EL MOCTAR, O.; SHIGUNOV, V. (2012a), *Rankine source method for seakeeping predictions,* 31st Int. Conf. Ocean, Offshore and Arctic Eng. (OMAE), Rio de Janeiro

SÖDING, H.; SHIGUNOV, V.; SCHELLIN, T.E.; EL MOCTAR, O.; WALTER, S. (2012b), *Computing added resistance in waves – Rankine panel method vs RANSE method,* 15th Numerical Towing Tank Symp. (NuTTS), Cortona

SÖDING, H.; SHIGUNOV, V.; SCHELLIN, T.; EL MOCTAR, O. (2012c), *A Rankine panel method for added resistance of ships in waves,* 31st Int. Conf. Ocean, Offshore and Arctic Eng. (OMAE), Rio de Janeiro

VARGAS, A.; SHAN, H. (2017), *Modeling of ship resistance as a function of biofouling type, coverage, and spatial variation,* 2nd Hull Performance & Insight Conf. (HullPIC), Ulrichshusen, pp.264-281

VARGAS, A.; SHAN, H.; HOLM, E. (2019), *Using CFD to Predict Ship Resistance due to Biofouling and Plan Hull Maintenance,* 4th Hull Performance & Insight Conf. (HullPIC), Gubbio, pp.242-253

How to Achieve Performance Optimization Potential Considering High-Quality Data

An ISO 19030 Use Case with an Exemplary Vessel-Specific Trim Map

Klas Reimer, Hoppe Marine, Hamburg/Germany, k.reimer@hoppe-marine.com

Abstract

This paper gives an overview of how vessel-specific trim maps can be created using validated operational data. Using reliable data for the trim optimization offers significant value for ship operators, ship owners and managers. As a first step, an existing draft measurement system can be enhanced by inertial measuring units to form a Dynamic Trim Measurement system. Combined with a shaft power meter and a speed log, a Dynamic Trim Measurement system is born, and a vessel specific trim map can be created. As a second step, a continuous data validation has been pointed out as a prerequisite for optimization. Thus, the data quality of main engine power, draft and trim as well as the ship's speed through the water (STW) play an essential role. Inadequately maintained sensor technology is often subject to an offset, an unnoticed long-term drift or dynamic influencing factors, which lead to a faulty measurement. But what does this mean in numbers? - A dynamic mis-determination of the STW of about 1 kn (16 kn real / 17 kn measured) for a 350 m sample container ship, with 20 kn design speed, already results in a performance determination error of more than 10 %. This value already exceeds the average optimization potential.

1. Introduction

The optimization of the ship's operation and performance in terms of emission and fuel reduction still is and will always be an omnipresent topic. One factor in terms of fuel consumption with high potentials for optimization, is the trim of the vessel that has a massive influence on the ship resistance. One possibility to increase the performance working with a vessel specific trim map. In terms of constantly varying operation and loading conditions, trim maps offer a high degree of information regarding power consumption of the main engine in combination with trim and draft, depending on the ship's speed.

Often data is used without prior validation regarding performance monitoring and optimization. The intention here is to save operational costs in a range of a few percent. The great amount of input variables sets high demands on the validity of sensor data. A lack of sensor maintenance often causes undesired offsets, dynamic errors or long-term drifts. Hence, with an unclean database any optimization efforts may even have negative effects on the operation of the ship.

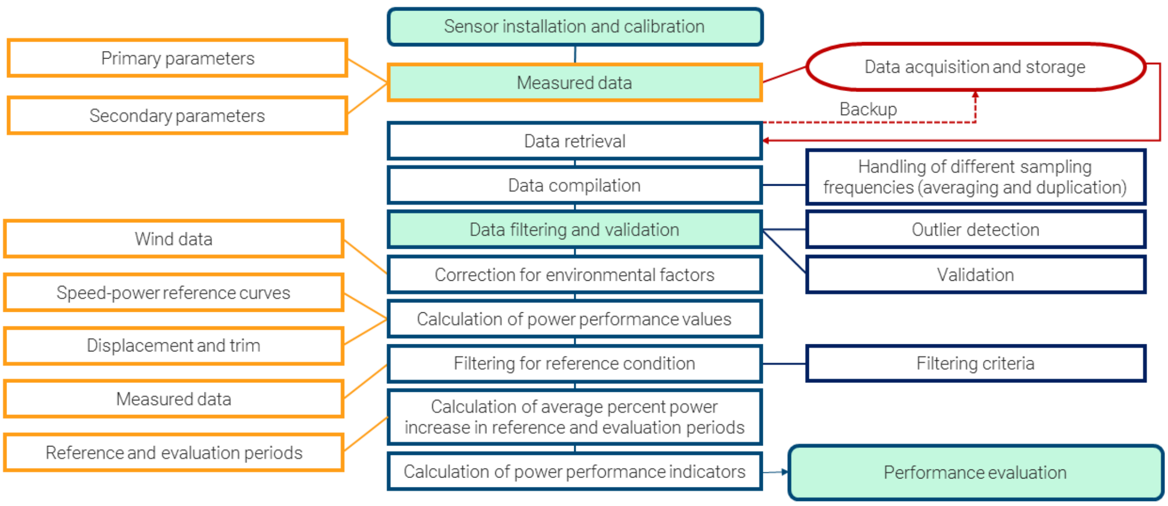


Fig.1: ISO 19030 flowchart

Only minor efforts and a pre-defined number of reliable sensors is necessary to create a ship-specific trim map for the resultant optimization of the ship's operation. To develop and to use algorithms for performance optimization, the awareness of maintaining a clean data base becomes more and more a paradigm.

In terms of data validation for optimized operations, working with validation and correlation algorithms is recommended. These algorithms have been developed by experienced marine engineers, navigators, service technicians and crew members. On the other hand, there are several guidelines and rules according to *ISO 19030 (2016)* that form an ideal base to start with. The ISO standard describes in detail how to filter and to process the recorded data in order to get calm water conditions. Only then it is possible to get comparable conditions for a later optimization, Fig.1.

2. Approach to trim optimization

It is only five steps to get high data quality to ensure optimization potential:

1. System needs to provide primary parameters (sensor installation)
2. Data needs to be validated
3. Data needs to be filtered
4. Data needs to be maintained
5. Data needs to be available

These will be outlined in more detail in the following.

2.1. Step 1 - System to provide primary parameters

ISO 19030 (2016) describes the following primary parameter: Speed log with STW, GPS data with heading and speed-over-ground, shaft power, rudder angle, wind and drafts. In this particular case, the case study 'Developing a trim map' is focused on the possibility for measuring dynamic drafts, dynamic trim by retrofit. Thus, besides the performance measurement, the basics for dynamic draft and trim measurements are enhanced by a validation.

A static draft measurement system can be enhanced by inertial measuring units to form a Dynamic Draft and Trim Measurement system. Often, ship lines or other hull descriptions used to derive a 3D model for numeric flow simulations are no longer available. As full-scale 3D scans are only possible during dry dock periods, a numeric determination of the trim map for retrofit solutions is often very costly. If a draft measurement system is already installed, the system could be enhanced by inertial measuring units, creating a system capable of determining the dynamic draft. In combination with a power meter, it is possible to create a ship-specific trim map during normal operation. Besides increasing the ship's efficiency, the operational costs can be reduced at minimum retrofit efforts.

2.2. Step 2 - Validated operational data

In case of non-ideal floating conditions, i.e. incorrect trim, a high resistance is affecting the hull. This inevitably results in an increase of fuel consumption, with a high potential for optimization. Hence, the reliably determined dynamic trim is a decisive variable to be considered for ship performance.

Trying to perform the trim correction with hydrostatically measured drafts can have negative impacts on the ship's operation, due to the fact, that hydrostatic draft sensors are based on the measurement of the surrounding pressure (water column). The water flow around the sensors during voyage results in a pressure impact. Depending on the mounting position and the related flow vector, these influences may vary considerably and may not be predicted reliably due to further influences in the boundary layer. This behavior can be explained with the law of energy conservation. If we consider an infinitesimal volume element, the energy of the fluid it contains remains constant over time. In a horizontal flow the total amount of energy is composed by the potential energy and the kinetic energy. The potential energy refers to the static pressure through the water column, whereas the kinetic energy refers to the dynamic pressure due to the flow.

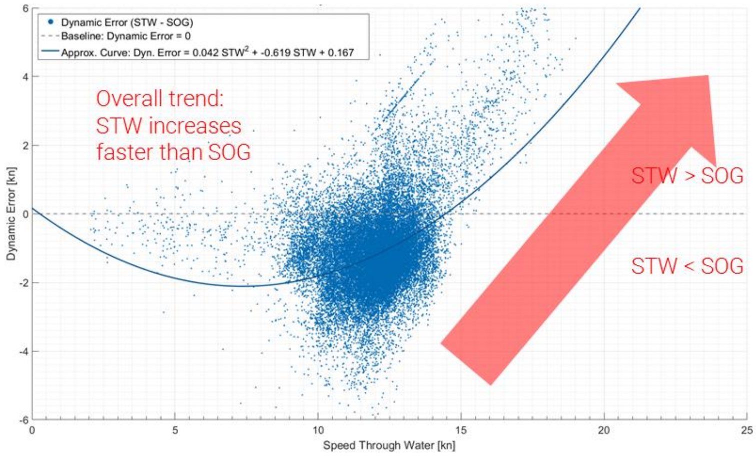


Fig.2: Highly dynamic change of the speed through water, compared to the speed over ground (SOG) for a multi-purpose freighter with a length of 150 m.

The most important factors influencing the dynamic draft measurement are:

- Speed through water
- Flow angle
- Sensor position alongside the ship structure
    - Acceleration of current at the bow
    - Deceleration of current at the stern
- Thickness of boundary layer at the hull
- Turbulences due to fouling
- Density variations of single current layers
- Heave sea
- Natural wave of the vessel

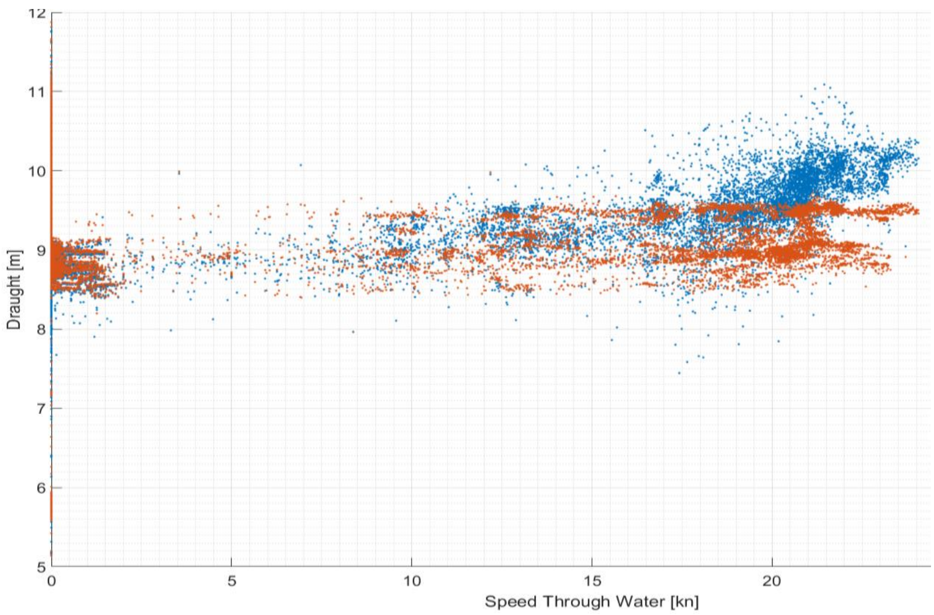


Fig.2: Blue indicates the statically determined forward draft which indicates large errors at higher speeds. Red indicates the dynamic draft. In this case, the measurement was determined by dynamic floating conditions using an inertial measuring units (IMU), albeit still without considering the bending line.

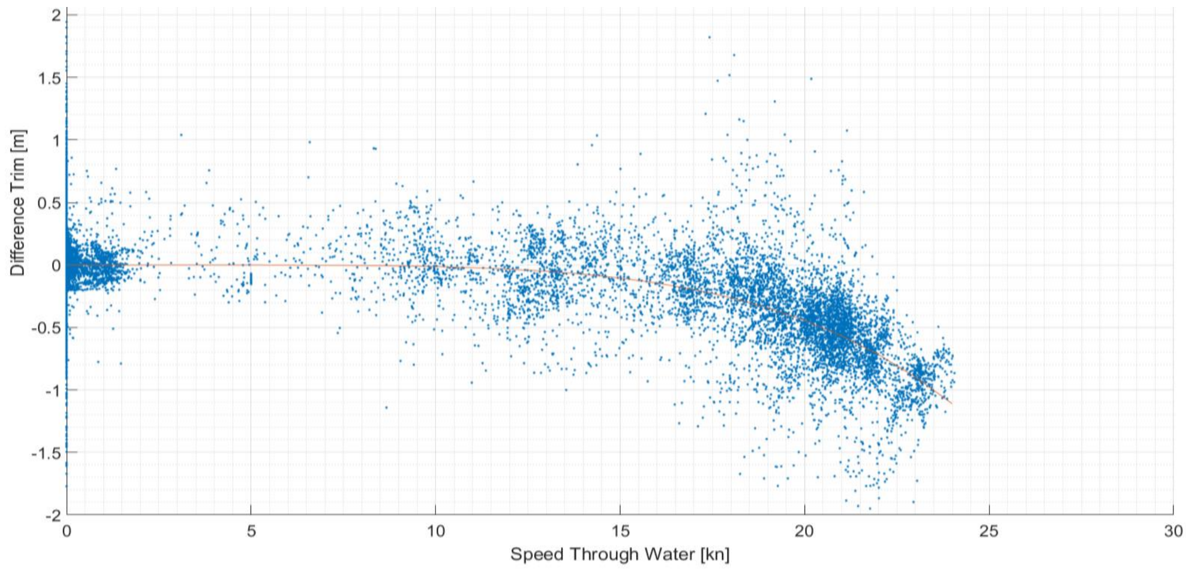


Fig.3: A proper draft correction according to ISO 19030 for creating data comparability is no longer possible. This error determination results in an unreliable determination of the trim.

The necessity of a dynamic draft measurement is reflected by the fact, that the trim must be determined by dynamic drafts that consider the bending line. Even though the load distribution stays constant during voyage, any change in ballast as well as water flow around the hull results in time and speed dependent changes of the trim. Therefore, the trim must be determined dynamically at any time. Only then, a significant trim map can be created.

2.3 Step 3 - Data needs to be filtered

Data can be filtered according to ISO19030. Contrary to common procedures with static drafts as input variables, dynamic drafts will be used in this case. In Fig.5, the results of data filtering are shown in dark red.

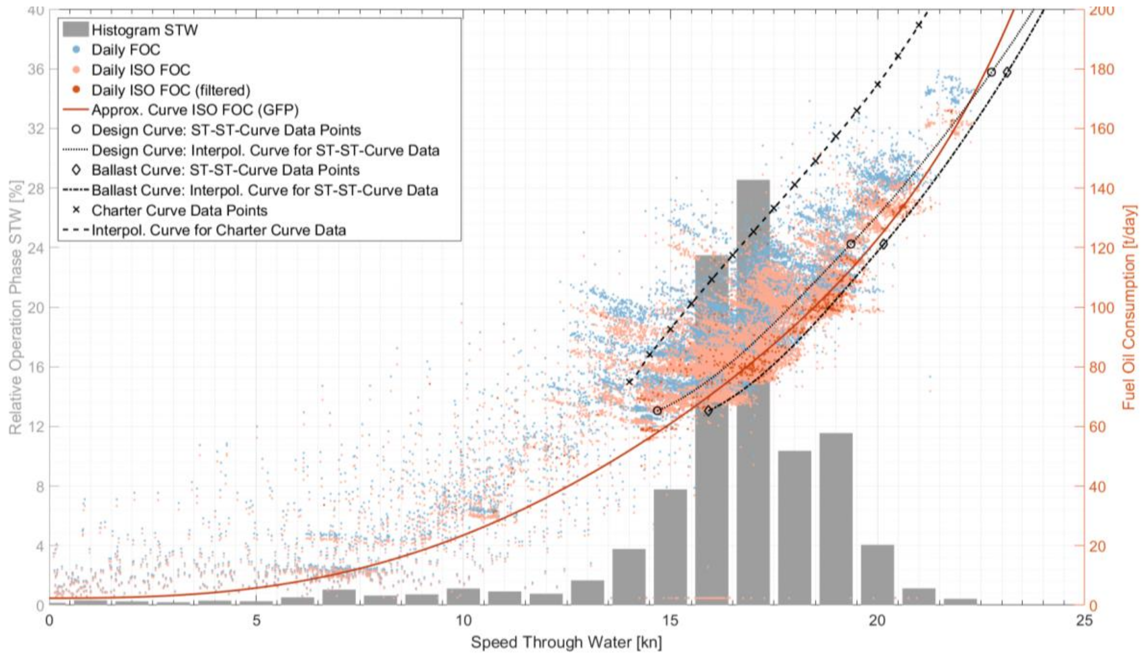


Fig.4: Effect of filtering (dark red dots indicate filtered data)

2.4 Step 4 - Data need to be maintained

Ensuring a clean and valid database that is oriented according to ISO 19030 forms the basis for any successful optimization. To ensure such a data quality in the long-term, continuous maintenance is essential. By enabling a daily monitoring of transmitted data in the first step, continuous maintenance should also enable possibilities for remote maintenance of onboard applications. In the occurrence of faulty functions that cannot be solved by remote maintenance or other contact with the vessel, onboard service work becomes necessary to re-establish clean data.

In case several vessels need to be maintained, the data validation might become challenging. Following a cascading procedure at the top level helps indicate the vessels with anomalies. In case the total data quality is below a pre-defined limit, a detailed vessel-specific analysis becomes necessary. In parallel, a correlation matrix is used to place primary parameter and further chosen signals in relation to one another. Especially in terms of abnormal primary parameter an in-depth validation with marine engineering analytic tools is required.

2.5 Step 5 - Data needs to be available

For a regular data validation, a high data availability is the decisive factor, *CML (2019)*. Even though a retrospective validation of logged data, with data probably been stored on USB storage devices and sent by mail, may also be quite useful, a prompt and timely action and the detection of abnormal behavior is not possible.

In terms of daily data validation on one hand it turned out, that 24h-aggregated values from noon reports are very useful for management and operation departments. On the other hand, noon reports allow data validation and plausibility checks only in a moderate way. For significant and representative evaluations aggregations of 60s are adequate enough, depending on the data source.

A ship-to-shore connection with fully encrypted transport is the appropriate medium. With a compressed data volume of max. 2 MB per day for values every 100 minutes, 25 values with data aggregation every 10 s as well as the 10 high-resolution ship motion data with data aggregation every second, transmission via V-Sat is possible without any problems.

3. Use Case as result: Exemplary vessel-specific trim maps

The preparation of a vessel-specific trim map, based on real and validated data, can be achieved by an exact dynamic trim- and draft measurement, *Harcke and Reimer (2019).* By such a trim map the optimal trim and thus the optimal operating point with lowest speed loss (i.e. the loss of speed compared to new building conditions) can be determined. With real operating data, power savings and reduced fuel consumption can be reliably achieved for the long term.

The challenge in using validated data is to check comparable operating conditions and to disregard varying environmental influences on the parameter, like on the main engine power, on the torque of the shaft or on the speed through water. To underline the importance of a clean data base two operating points are considered in Fig.6.

If this behavior is transferred to a faulty or missing data validation although apparently operating with best trim determined by hydrostatic and faulty draft values, the trim could lead to a disproportionally high fuel consumption. When utilizing a trim map and when creating individual maps with real data, a sophisticated dynamic correction of drafts over the vessel's trim is therefore essential.

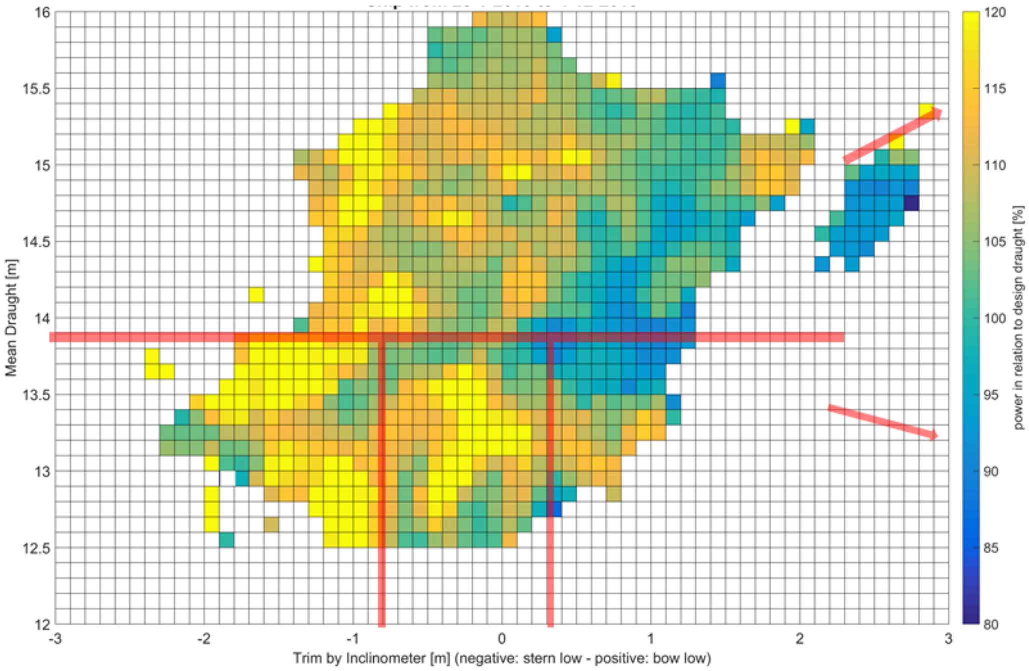


Fig.5: Optimal and suboptimal trim is sometimes close to each other. The change from blue to orange areas results (at similar operation) in ~30% higher power demand at design speed.

4. Outlook – Future applications

The data acquisition of drafts, measured by Hoppe Marine, includes a self-validation, *Harcke (2019)*, and internal status communication via a "validity flag". To assure a clean and complete data set, the next step in development is to enable sensors and data processing to autonomous forecast of its conditions. This procedure enables a predictive maintenance of sensors, by which failures or limit exceedances can be avoided. In this way, on board services and material supply can be better planned and performed at logistically well-connected sites.

With the ability to most-accurately determine the vessel's trim during the voyage, the information may also be provided for Autoballasting and Autotrim systems.

In the future, those systems could be used to autonomously set the optimum trim condition at any time. In this case, watch times could be used more efficiently, due to the fact that no manual interaction for ballast and trim operation is needed. In combination with tank measuring units and valve- and pump control units for ballast water systems, setting up the trim could become a more and more automated process. This functionality can be realized by interfacing the loading computer. In this case the sequentially driven pumping operations must be controlled in a way, that limits for bending and torsion, which are set and determined by the loading computer, are not exceeded at any time.

References

CML (2019), *„Ship Operation 4.0" . Datenbasierte Effizienzsteigerung des Schiffsbetrieb*, Fraunhofer Verlag, pp.5-6

HARCKE, N. (2019), *Einfluss der Datengüte auf die Optimierung des Schiffsbetriebs*, Schiff&Hafen, June, pp.24-26

HARCKE, N.; REIMER, K. (2019), *Den richtigen Trimm finden*, Hansa, October, pp.52-53

ISO 19030 (2016), *Ships and marine technology — Measurement of changes in hull and propeller performance—Part 2: Default method*, Int. Standard Org., Geneva, p.3

Uncertainty of Speed Trials

Sofia Werner, **Lars Gustafsson**, SSPA, Sweden, sofia.werner@sspa.se

Abstract

A collection of speed trials with corresponding model test predictions is utilised to examine the procedures and standards for speed trial conduct and analysis. The precision error of speed trials is estimated using series of sister ships and the implication on EEDI verification and CFD/EFD validation against speed trials is discussed. The effect on the speed trial results of using an empirical wave correction method instead of ship specific seakeeping model is shown for one example. The approach of averaging the true wind from the up and down-wind run in a trial is compared to the traditional method of not averaging.

1. Introduction

A sea trial is a test program in which the ship builder demonstrates that the vessel performs according to the contract before the ship is delivered to the ship owner. One out of several parts in a sea trial program is the speed trial, in which the speed-power-rpm relation is confirmed. This is also the occasion when compliance with the EEDI-regulations is verified. It is of high important to all stakeholders that the procedures for conducting and analysing the speed trial are accurate and precise.

ITTC published in 2014 new Recommended Procedures for Conducting and Analysing Speed Trials, which were followed by the identical ISO 15016 in 2015. These procedures are mandatory to follow when verifying the EEDI speed. The main differences from earlier standards are new methods for eliminating the effect of waves, wind and current. The new methods have been discussed in the shipping community and concerns have been expressed (mainly from the yards) that the new methods are conservative.

The ISO standard and the ITTC procedures aims for a "target accuracy of within 2% in shaft power", *ITTC (2017b), ISO (2015)*. Nothing is however said about the precision. The contract between the ship builder and the buyer normally includes a margin which gives room for some uncertainty. The EEDI regulations are less allowing, the derived EEDI-value must be less than the required. This means that the builder needs to take the uncertainty into account as a safety margin and design a ship that performs better than the required EEDI level.

Speed trials are vital for correlation of the model test extrapolation methods used by all towing tanks. Occasionally, speed trials are used to validate CFD methods for prediction of propulsive power. For these purposes it is valuable to be aware of the uncertainty that can be expected for speed trial results.

SSPA possess a database of speed trials with corresponding model test predictions. In this paper the database is used to investigate some of the doubts that have expressed regarding the new correction methods, and to shed some light on the expected uncertainty of speed trials in general.

2. Data set

The analysed data set consist of 183 speed trials carried out between 2006 and 2019 at 21 Asian shipyards. The vessels are all common cargo vessels with Lpp ranging from 100 m to 355 m and block coefficients between 0.5 and 0.84. The trial reports were provided to SSPA either by the yards or by the ship owners.

The data was re-analysed with SSPA in-house software according to ITTC 7.5-04-01-01 / ISO 15016:2015. The trials performed before 2015 were conducted according to respectively builders' practice, which are not always in agreement with the new standards. However, all trials included in the data base fulfil the new standards limits on weather condition. Trials with obvious poor quality or missing information have been omitted from the data set.

The corresponding model tests were carried out in SSPA's towing tank (260m x 10m x 5m) and analysed according to 1978 ITTC Performance Prediction Method, *ITTC (2017a)*, using CFD and EFD combined methods for form factor determination.

3. Uncertainty estimation

The uncertainty of speed trial results stems from the uncertainty of the measurement equipment onboard, the observations of wave condition and the methods for estimating the environmental corrections. Some of the methods are based on empirical models derived to be accurate on average for a population of ships. Last but not the least, the ship as built may deviate from the original design even between sister ships. Different weather condition when the hull coating work is carried out could for example be one factor that contribute to this. Biological growth during the time between dry dock and trial could also be an explanation. The yards' strategies for hull cleaning before the trial seams to vary depending on the time of the year, availability in the dry dock and possible risk to fail the trial.

The precision error can be estimated using series of sister ships. In the present dataset there are 14 series with 5 sisters or more in each series. Fig.2 shows the precision error (2 times the standard deviation) on the power. The precision error is between 5% and 12% with the median of around 8.5%. This agrees well with *Wienke and Lampe (2016)* who found a precision error of 6.5% for 3 series of container vessels and *Insel (2008)* who reported a precision error of 7% for a series of ferries.

Fig.1 gives the distribution of the normalised power for 8 series of sister ships with 6 or more sisters in each series. This clearly displays the large spread and extreme outliers that can appear in a series of sister ships. If one of the outliers were the first vessel built in a series, the builder and the model test facility would be heavily questioned. The lesson learned is that we should be careful to draw conclusions based on one or even a few trials.

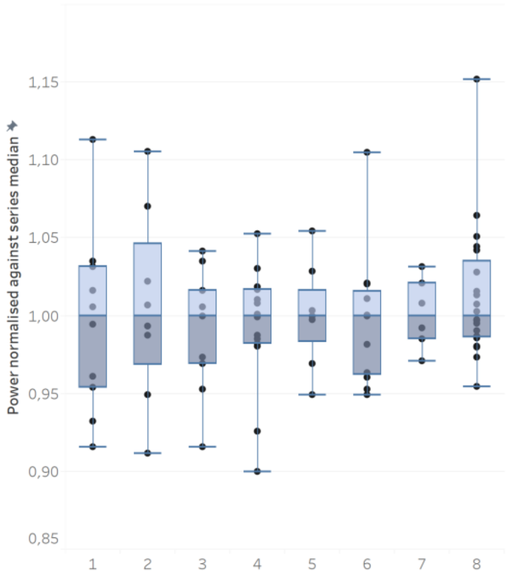


Fig.1: Speed trial power normalised against median of series for 8 sister ship series with 6 sisters or more in each series. The boxes indicate the middle quartiles.

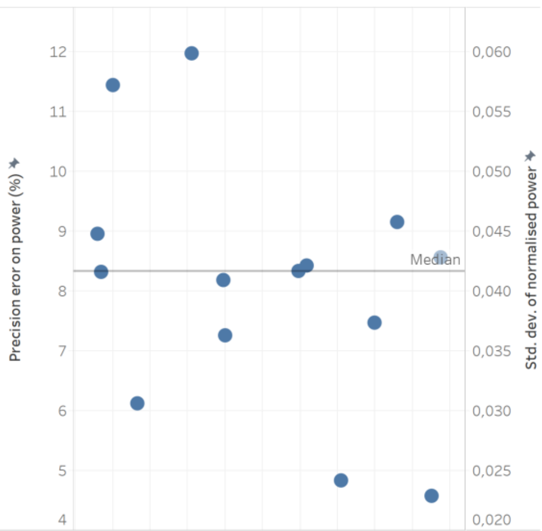


Fig.2: Precision error and standard deviation of speed trial power of 14 sister ship series with 5 sisters or more. Sorted on ship length with shortest (~180m) to the left and the longest (~350m) to the right.

The introduction of the new standards for speed trial conduct and analysis in 2014/2015 came with a hope that the quality of speed trials would increase in general. The present dataset cannot reveal any such trend, neither for the sister ship series or the spread of the total propulsion. It could be that the dataset is too small and the changes are too close in time.

Fig.2 suggests that there may be a relation between precision error and ship size, although the dataset is far too small to draw firm conclusions. It would be reasonable that the influence of waves affects a large vessel less, and we know that the wave correction is one of the largest sources of uncertainty (Insel 2008).

Precision is only one part of the total uncertainty. The other part, accuracy (bias) is harder to quantify. The ISO and ITTC standards claim that the target accuracy is 2% on the power. *Insel (2008)* used a Monte Carlo approach and estimated the bias limit to 3-5% of the power. This was based on the previous speed trial analysis procedures; it would be interesting to see it repeated with the new standards.

Combining the numbers for precision from the current study and the bias estimated by Insel gives a total uncertainty of $(8.5^2\,\%+4^2\,\%)^{1/2}$ =~10%.

4. Correlation of model test power predictions

Correlation with speed trial data is an important part of the model test extrapolation procedure. According to ITTC Recommended Procedures the correlation factor (ITTC 2017c) is "a correction for any systematic errors in model test and powering prediction procedures, including any facility bias." Each model test facility derives their own correlation factors specific for their facility. ITTC or IMO does not prescribe any values.

There are three alternative approaches and the model test facility is free to choose one, but only one, of them:

- C_P and C_N, factors that are multiplied to the power and shaft rate as the last step in the scaling procedure
- C_A, which is applied to the resistance prediction
- ΔC_{FC}- Δw_C, corrections on resistance and wake component

In any case, the correlation factors should be based on a large number of speed trials with corresponding model test predictions. For the C_P - C_N option, the factors are derived by taking the corrected power from a speed trial divided by the power predicted from the model test (without the correlation factor applied):

$$\mathrm{C_P} = \frac{P_{D\_trial}}{P_{D_{Tank\ without\ correlation\ factor}}}$$

and the corresponding for the shaft rate. The powers are extracted from the faired curves at 75% MCR, as illustrated in Fig.3.

The fraction is computed for a large number of cases and the determined C_P is the assembled value. At SSPA, C_P is derived as the median of all trials of enough quality (around 100 points). This means that statistically only 50% of the trials will pass the target speed at the trial. The builder's contract with the buyer must include enough margin to allow for this.

If the correlation factors are derived based on the best quartile of the statistics, it is only 25% change to meet the predicted speed at the speed trial. The yard takes a larger risk to fail the trial, but the ship performance better on paper.

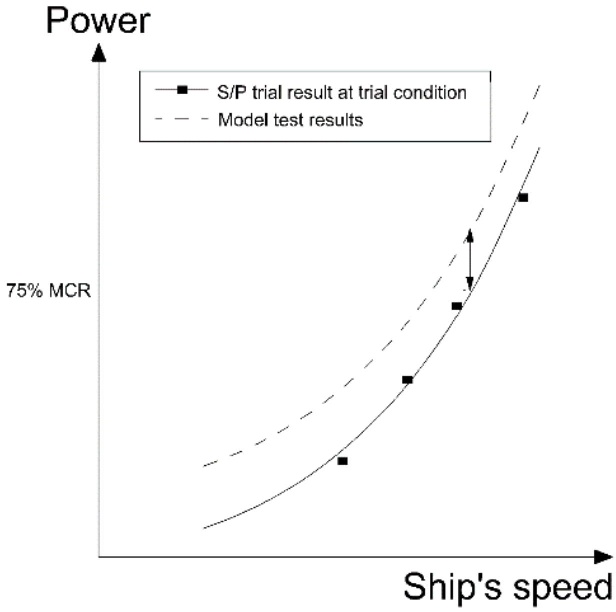


Fig.3: Correlation of model test power and corrected power from the
speed trial power, taken at the faired curve at 75% MCR.

One needs to be very careful if using customised correlation factors for individual yards based on speed trial data from that particular yard, for example with the argument that this yard has higher building quality than others (judged by the yard itself). This is a questionable approach since it means the dataset will be rather small, and above all, the model test facility has no control of where the hull form will be built in the end and to what quality.

We recommend ship buyers to request information on how the correlation factors are derived, based on what dataset and whether it is the median value or not.

Fig.4 shows the data set used at SSPA to confirm the correlation factor C_P. The results are presented as a prediction correctness factor PC:

$$PC = \frac{Corrected\ Speed\ Trial\ Power}{Predicted\ Power\ from\ model\ test}$$

both derived at the EEDI speed, i.e. corresponding to 75% MCR from the faired speed trial and model test curves, as illustrated in Fig.3.

Fig.4 confirms that the average Prediction Correctness is close to 1, which means that the model test predictions are accurate *on average*. For individual ships divergences from the model test prediction up to 5-10% is normal. Note that this spread to the largest extent is due to the uncertainty of the speed trial and differences in building process, as was show in the earlier section on sister ships series. The mean Prediction Correction index for the sister ships series are all close to one.

The Uncertainty Index on the x-axis is an in-house developed index that indicates the trustworthiness of a speed trial and to point out which speed trials that should not be considered when extracting general conclusions. It summarises the largest error sources and weigh them according to their impact on the result for each individual trial. The main sources of uncertainty are usually large wave and wind corrections due to adverse weather conditions.

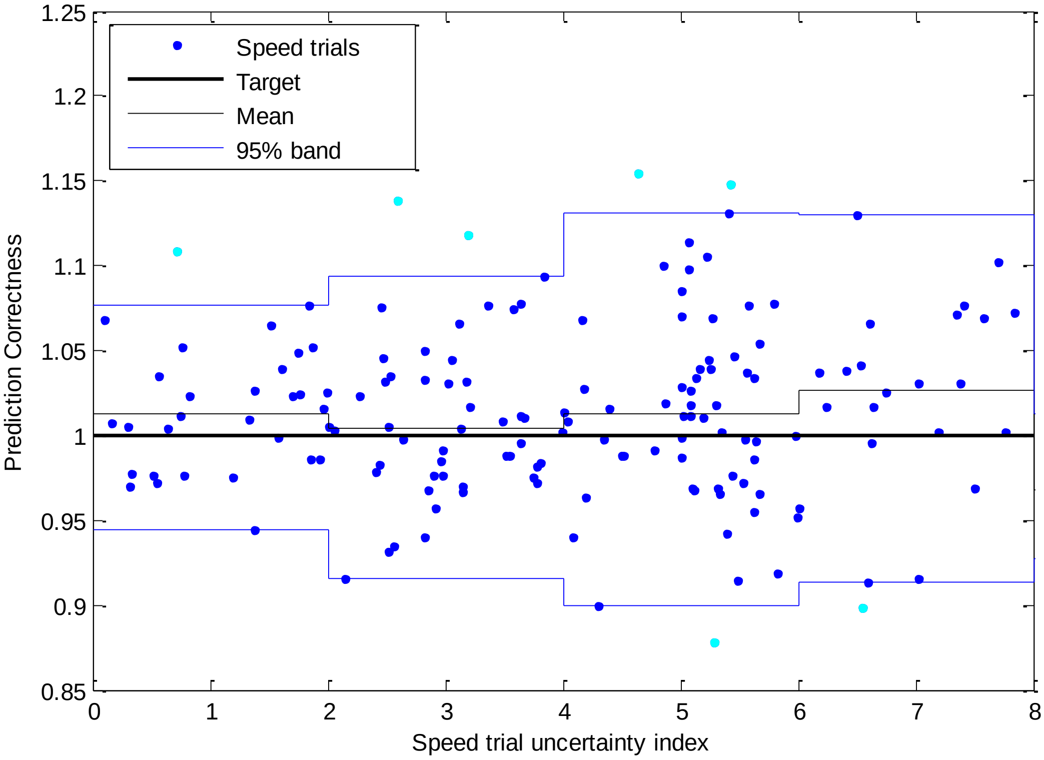


Fig.4: Confirmation of model test correlation. Note that the spread is due to precision error in speed trial test and building process.

SSPA's data set does not support any trend either with ship type, size, scale factor, dimensionless parameters, number of propellers or speed. This indicates that the extrapolation method including form factors derived with combined CFD and EFD account for the various scaling phenomena in a sufficient way, on average. The only trend that can be detected is a slight reduction of spread for larger vessels, which probably is due to smaller effect of waves.

5. EEDI verification and validation of CFD and EFD

The precision error derived based on series of sister ships includes not only the precision in the speed trial test but of course also any physical difference between the sister ships. From EEDI verification point of view it would be an advantage if we could separate these components and build the trial precision error into the regulations. To acquire such knowledge, we would need to conduct a large number of speed trials with the same vessel, which would be hard to realise in practice.

From CFD and EFD validation point of view the distinction between the trial precision and spread in the building process is irrelevant. Both components are included in the validation uncertainty. The important point is to consider the data uncertainty in validation exercises at all. This means that based on 1 speed trial, predictions from CFD or EFD can only be validated to ~10% on the power. To be able to validate to for example to 1% would require 100 trials for the given ship, to 2% we need 25 trials. This would prove that validation is achieved for that particular hull form, but not necessarily for another similar ship. To demonstrate the ability to predict the power with CFD or EFD on a general level, a large number of speed trials of different hull forms are required.

6. Wave correction methods

The EEDI-value is defined for calm water and no wind. The speed trial may be carried out at wind speeds up to Bf 6 and wave heights 2-3m depending on ship size. The effect of wind and waves is removed from the measured power using estimations of the added resistance due to wind and waves. In the ITTC Recommended Procedures and the ISO standards there are four methods for wave correction, which all involves estimation of the added resistance due to waves:

1. Simplified method for trials with limited heave and pitch (STAWAVE-1)
2. Empirical method based on regression of model tests in waves (STAWAVE-2)
3. A combination of a theoretical method and limited towing tank tests in short waves (NMRI)
4. Seakeeping model test in regular waves for the actual ship

The most commonly used in the industry is option 2, STAWAVE 2, (at least among SSPA's connections) and this is the method used by default in SSPA's in-house analysis. As it requires only a few geometrical parameters for the actual ship, it is convenient to use, but the accuracy must be considered especially for wave heights close to the upper limit. In 2014, ITTC Specialist Committee on Performance of Ships in Service carried out a validation study where predictions using the STAWAVE 2 method were compared with seakeeping model test, Fig.5. For many cases the STAWAVE2 prediction is almost doubled the value from the seakeeping tests whereas for some cases it is half of it.

Ship owners that are concerned about accurate speed trial results can request dedicated seakeeping model test to be carried out before the trial. This gives the most ship specific wave correction of the available options. As an example, Fig.6 shows the speed trial results of a series of sister ships corrected with STAWAVE2 as well as with added resistance from seakeeping model test of the actual ship. In this case the STAWAVE2 predicted an added resistance RAO that was about half of the one derived from the ship specific model test for all wave lengths. This means that the wave corrections are smaller with the STAWAVE2 method and hence the corrected power from the speed trial larger. If the correction works as it should, all points in Fig.6 should be on a horizontal line. For the trials where the wave height was less than 1 meter, the difference is neglectable. With both methods, the target power is met. As the wave weight increase, the difference grows. For the trials conducted in 2.5m waves, which is still below the maximum limit for this vessel, the derived power is about 8% higher than the target when using the STAWAVE2, but very close to the target when using the sea keeping model test. Without the seakeeping model test, the performance of some of the sister vessels in this fleet would appear to be considerably worse than the others. This would affect the base line, and probably the buyers satisfaction. This is also an example of how the correction methods adds to the precision error.

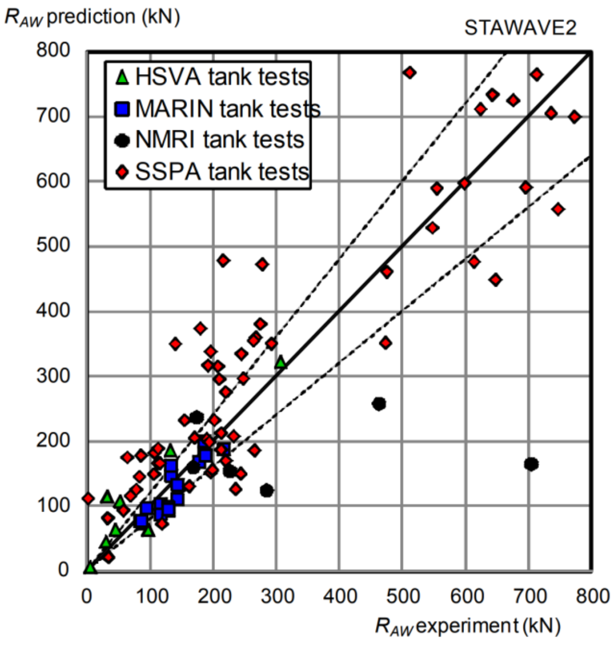


Fig.5: Correlation of added resistance in irregular waves predicted with STAWAVE2 ("prediction") and model test ("experiment") for various ship types, loading conditions and speeds. *ITTC (2014)*

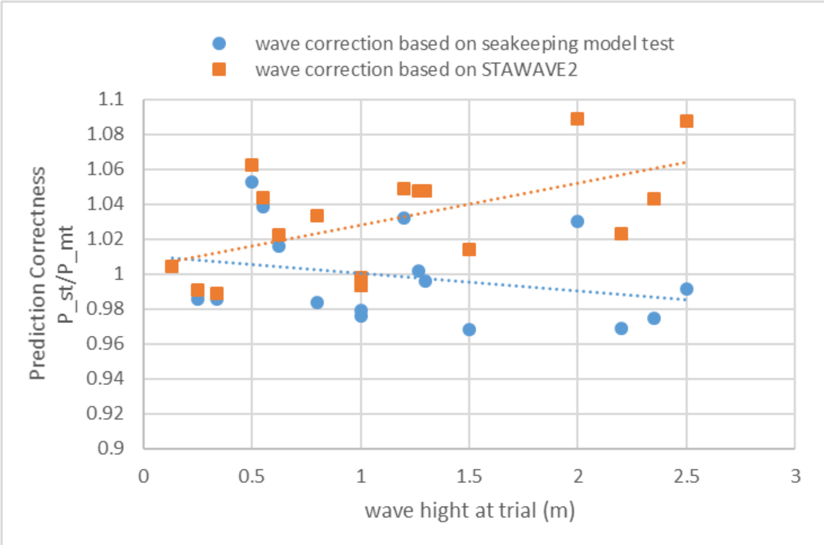


Fig.6: Normalised speed trial power for a series of sister ships using either STAWAVE2 empirical method or dedicated seakeeping model test.

7. Wind correction methods

A speed trial is conducted by setting the vessel on a straight course against the wind and waves for a 10 minutes run, then turn 180° and sail back on a reciprocal course for the counter-run. A typical trial consists of minimum 4 such double runs. The added resistance due to wind needs to be removed from the measured power and therefore the wind is measured with the ship's anemometer during the trial. The natural true wind is then deduced by subtracting the ship's speed vector from the measured wind vector.

It is very common that the computed true wind comes out as the example in Fig.7. Each point in the figure represents the true wind speed averaged over a single run. Obviously, this is incorrect. The true wind should vary smoothly, independent of what the ship is doing. The reason for this phenomenon could be asymmetric disturbance from the ship superstructure on the anemometer, or less accurate anemometer readings for the low relative wind speeds at the downwind legs.

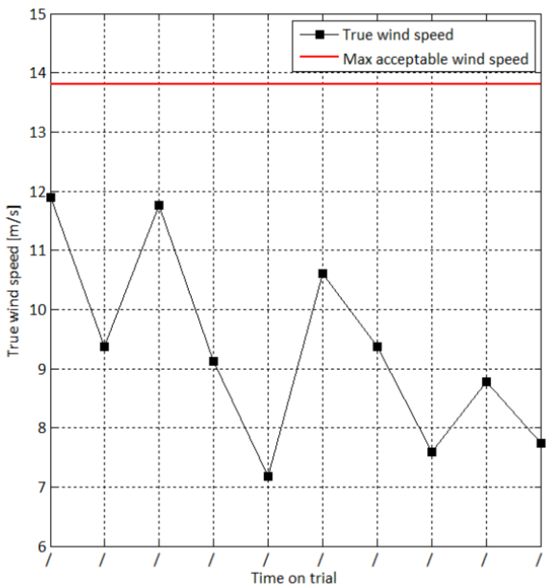


Fig.7: Example of derived true wind from a speed trial when the up and down wind legs are not averaged.

To counter-act this phenomenon, the ITTC and ISO standards prescribe that the calculated true wind is averaged over each double run (one up-wind and one down-wind leg). This practical engineering approach has been criticised for being theoretically incorrect. The main concern has been if it leads to conservative bias error which reduces the achieved ship performance on paper.

In order to investigate whether this fear is entitles, all speed trials in SSPA's database were reanalysed without averaging the true wind and the results compared to that of the prescribed method.

Fig.8 shows the difference in power (%) between the result from averaging wind and not-averaging. The following observations are made:

- 72% of the cases are within ±2% power difference.
- The median power differs by 0.4%. This means that if the "No Averaging" procedure is used, the obtained power is 0.4% lower - on an average level of this population.

Considering the precision error of the data and the general accuracy target of 2% on power, this result suggests that there is no bias effect of using the average process, neither over-prediction nor under-prediction, when viewed over the whole population (this propulsion, that is).

The cases with large difference between "Averaging" and "No Averaging" are examined closer. It turns out that many of them are from 4 series of sister vessels. This could point at some systematic weakness of the anemometer position on these ships.

Many of the cases with differences lower than -2% all have that in common that the speed trials were performed in medium to strong wind from the side. With the wind-averaging method, the wind corrections are small in both directions. If the wind is not average, the wind corrections are fairly large in both directions. This makes the large difference in power. The new ITTC and ISO standards prescribe that the speed trial runs "preferably be carried out by heading into and following the dominant wave or wind direction, depending on which effects the ship's speed most." The situation of strong wind perpendicular to the direction of large waves should be fairly uncommon, making this situation rare if the new standards are followed.

If the wind changes significantly in the time between the runs in a double run, averaging will of course under-predict the wind in one run and over predict in the other. Since the drag coefficient is different for the two runs, the two errors will not level out perfectly. If the wind measurements on-board are undisturbed, it is more accurate not to average the wind in such circumstances. However, as soon as the wind measurements are disturbed, which seems to the most common case, that error is probably dominating or of the same size as the averaging error due to changing wind. More research is needed to determine the trade-off between those two error sources.

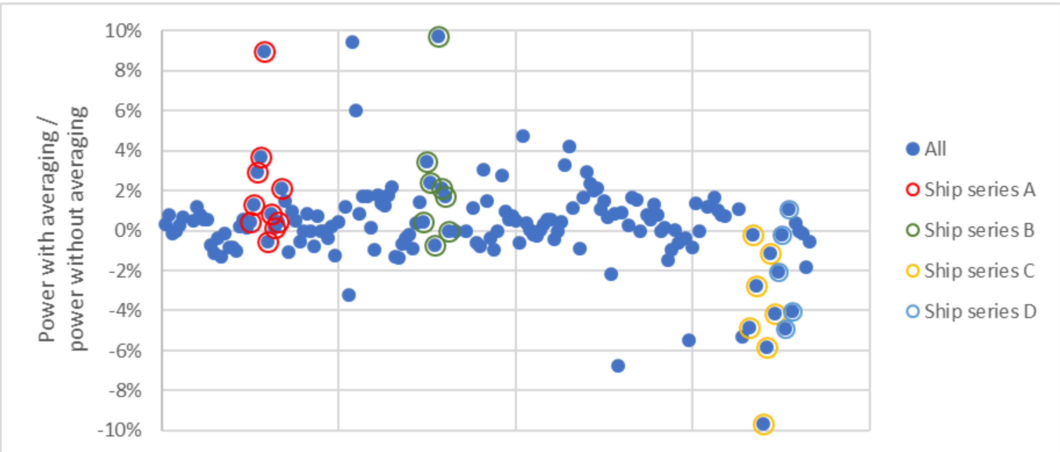


Fig.8: Comparison of wind correction with averaging up and down run against no averaging.

8. Conclusions

A data set of 183 sped trials of commercial vessels from different shipyards have been used to investigate issues regarding speed trial procedures in practise.

Based on 14 series of sister ships the precision error is estimated to be between 5% and 12% with the median of around 8.5%. Outliers of 10% from the median is not uncommon. This is in line with what others report in literature. Combining these figures for the precision limit with estimates of the bias limit by Insel (2008) gives a total uncertainty of 10%. This includes the measurements and weather observations during the trial, methods for analysing the results, and geometrical difference between the sister ships. It is not possible to separate these effects.

Predictions from CFD or model test can only be validated to ~10% on the power when compared to 1 speed trial result. To be able to validate to a lower uncertainty would require 100 trials for the given ship.

A comparison between the power derived from speed trials and the predicted power from model test shows that the predictions are correct *on average* for the whole population. The individual trials results can differ typically up to 10%, due to the uncertainty of the trial and the building process.

The analysed data set does not support any dependency of the model test correlation factor C_P either of ship type, size, scale factor, dimensionless parameters, number of propellers or speed. This indicates that the extrapolation method including form factors derived with combined CFD and EFD account for the various scaling phenomena in a sufficient way, on average.

The wave correction method STAWAVE2 is based on regression of model test of a large group of ships. It is accurate on average but for individual hull forms it may differ considerably compared to ship specific sea keeping test. One example is given where this leads to difference on the derived speed trial power of 8%. It is recommended to ITTC to reconsider the limits of acceptable wave heights when STAWAVE2 method is allowed to be used.

The method of averaging the true wind over two runs in a speed trial is compared to that when the true wind is used run by run. The results show that for the investigated population the wind averaging process does not give neither optimistic nor pessimistic result compared to the no-averaging process.

References

INSEL, M. (2008), *Uncertainty in the analysis of speed and powering trials*, Ocean Engineering 35

ISO (2015), *Ships and marine technology – Guidelines for the assessment of speed and power performance by analysis of speed trial data*, ISO 15016:2015

ITTC (2014), *Proceedings of the 27th Conference, Report of Specialist Committee on Performance of Ships in Service*

ITTC (2017a), *Recommended Procedure 7.5-02-03-01.4, 1978 ITTC Performance Prediction Method*

ITTC (2017b), *Recommended Procedure 7.5-04-01-01, Preparation, Conduct and Analysis of Speed/Power Trials*

ITTC (2017c), *Recommended Procedure 7.5-04-05-01, Guidelines on the determination of model-ship correlation factors*

WIENKE, J.; LAMPE, J. (2016), *Energy Efficiency Design Index in View of Performance Monitoring,* HullPIC 2016

Assessing Good & Bad Performers at Tanker Pools

Richard Marioth, Idealship GmbH, Itzehoe/Germany, rm@idealship.de

Abstract

Ship owners who place their tanker vessels in tonnage pools participate in the earnings and the operational expenses of the pool. The ship owner's income depends on several factors. One of them is that the ship owner is rewarded or penalized for the measured performance of his vessels through half yearly pool adjustments. This paper describes several principles that tanker pool managers use to determine the performance of the vessels under their commercial management. Challenges related to the assessment process are illustrated.

1. Introduction

1.1 Vessel tonnage pools

At vessel tonnage pools various owners place their vessels under the care of a single administration company, the pool manager. The vessels are commercially operated by the pool manager, who takes an administration fee, whereas the technical management remains with the ship owner, Fig.1.

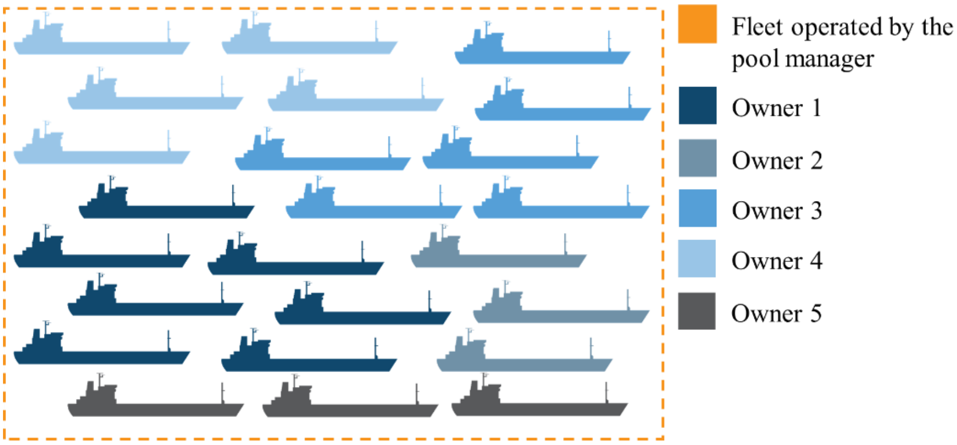


Fig.1: A tanker pool setup

There is a strong commercial commonality between pooled vessels and typically the pools are dedicated to a certain tanker size, e.g. Handysize vessels or Suezmax, *Ward (2015)*. Pool manager companies are e.g. Navig8, Scorpio, Maersk Tankers, and Teekay.

1.2 Pool points

Pool managers differentiate the usability and the commercial performance through so-called pool points. They are used as a factor in the vessel earning equation and reward or penalize for certain aspects. In the earnings equation, the pool manager first calculates the average net earnings per vessel per day, by summing up the revenues and deducting all costs. Besides the time spent in the pool, it is primarily the pool points that influence each ship's share of the net earnings of all ships in the pool. Most tanker pools distribute their net earnings based on the following formula:

$$VesselEarnings = \frac{(Vessel\ Days\ in\ Pool)}{\sum(All\ vessel\ days\ Pool)} \cdot \left(\frac{PoolPoints_{Vessel}}{PoolPoints_{Average}}\right) \cdot PoolNetEarnings \quad (+Factor)$$

It is common practice to award pool points for vessel characteristics that are beneficial for the pool. Most pools use 100 as base pool point figure for each vessel, *NN (2016)*. So every pool point that is given or deducted, increases or decreases the vessel earnings by roughly 1%.

Only a few pools use additional calculation variables besides the pool points, (i.e. an additional factor of the equation). In general, the criteria for awarding pool points is very different from pool to pool and not always set out in a transparent manner by the pool management, *Ward (2015)*.

Assuming a ship has the basic characteristics that fit the profile of the pool, the pool managers will award points based on one or several of the below categories:

a. Fuel performance (e.g. Speed & Consumption)
b. Physical vessel parameters (e.g. ice class, age, size)
c. Commercial & operational parameters (e.g. vetting, able to burn ULSHFO in port)

While the physical vessel parameters and the commercial flexibility parameters are somewhat static and usually set when a vessel enters the pool, the fuel performance can vary significantly over time. The main reason is that the hull and propeller performance changes over time due to fouling and paint degradation. Therefore, in order to avoid any inequity, it is necessary for every pool to have an adjustment or correction process to retroactively amend the pool points or other factors in the earning equation during the year, *NN (2016)*. In the following a few principles and methodologies about the approaches used by pool managers to assess the fuel performance are described, reflecting our understanding of the common business practices.

2. Fuel performance assessment principles

The pool manager needs to account for differences in fuel performance between the vessels of the pool participants on a regular basis. Even though the vessels have similar sizes, the actual operation pattern can vary a lot. The pool managers have the same challenge as many others in the industry: They need to determine the actual fuel consumption for vessel operations, that are highly impacted by external factors like weather, currents, cargo and commercial operation.

2.1 Gather data

Data is gathered by the pool manager through a separately installed noon reporting system onboard of the operated vessels or by a process where the vessel crew mails certain information daily to the pool management. Automatic data acquisition is not very common yet, but first systems are installed. For instance, the Navig8 pool installed some hardware which could be used for verification purposes . Many pool managers use nowadays the support of 3rd parties specialized in vessel performance analytics or weather evaluations for their performance assessments. Several pool managers use hindcast weather data to verify or to reduce the impact of the crew's manual inputs on the result.

2.2 Validity of data

To allow an appropriate comparison, the reported observations at sea used for the evaluation should have a limited impact of weather and other operational matters. Pool managers use filters, that apply in the same way for all operated vessels and reported evaluations. An observation is regarded as valid when the weather has had limited impact and the overall reporting conditions can be regarded as stable. However, different reporting systems and calculation methodologies are used between the pools. Due to this, each pool has its own way of differentiating between valid and not valid data.

2.3 Exemption periods

Apart from the filters on an individual report level, there can be certain periods when it becomes necessary to exempt a vessel from the pool evaluations, either for commercial reasons or as they would not allow a realistic analysis of the hull & propeller performance. For instance, when a vessel was on technical off-hire or trading in ice. Many pools have an idle clause in their pool agreements, that considers to a certain degree the impacts of biofouling and marine growth. Such clauses could state e.g. that when a vessel was put idle for four weeks in tropical waters and an impact of fouling on the hull &

propeller performance is evident, then the following sailing periods are exempted until the vessel was cleaned. The reported consumptions within such exempted periods are not used within the evaluation process.

2.4 Determine fuel consumptions

The goal of the pool manager is to evaluate the technical performance of all major consumers onboard of the vessel, i.e. the main engine, the auxiliary engines and the boiler. It is common practice that the manager runs the performance assessment on a semi-annual basis. If the pool manager is not able to determine the fuel performance of an evaluation period, e.g. when the vessel was sailing for a too short period within the pool, then either the fuel performance figures of the last assessment or the figures of a sister vessel are used at the pool point calculations.

The methodologies to determine fuel consumption figures developed by the pool managers distinguish between in-port consumptions and consumptions at sea. Whether cargo operational requirements (e.g. heating) and vessel manoeuvring consumptions are considered in the calculations or excluded completely can differ from pool to pool. Section 3 describes a few methodologies that the pool managers use to evaluate the fuel consumption at sea.

2.5 Actual or simulated operation

Pool managers can either use methodologies based on the actual operation of each vessel within the evaluation period or methodologies based on a common reference operation condition.

Using the actual operational profile of each vessel passes a bigger share of the potentials and the risks of how the vessel is operated to the pool members, as fuel consumption depends significantly on the operation patterns. E.g. a vessel that has a poor hull & propeller performance would not be penalized much in case it was mostly idle within the evaluation period. However, if such a vessel steams a lot, then this has a negative impact on the pool members earnings for that vessel.

To split the operational risk over all pool members, many pool managers simulate the vessel operation over a common operational or voyage profile. Such profiles give a weighting factor for each vessel operation like percentage of sailing in Ballast, percentage of sailing in Laden, etc., Fig.**2** (left). The weighting factors should reflect the typical vessel operation within the pools.

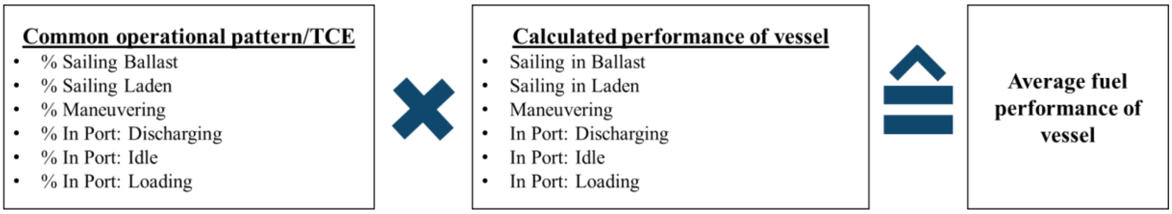


Fig.2: Simulated operation

A few pools use simply the fleet wide average of operation time for each condition as the common profile for all pool vessels. However, most pools base their pool point system on one or several Time Charter Equivalent (TCE) voyage profiles. The TCE calculation describes a vessel's voyage. E.g., it could be defined as a roundtrip from New York to Miami, 1 day loading, 1 day discharging and 2 days idle. The TCE also includes the voyage earnings and other expenses. On first sight, using TCE profiles seems more complex from a technical perspective, but the advantage is that the TCE is a well-known calculation in commercial tanker business and commercial operators can refer to this number very well.

Using simulated approaches, TCE or average percentages, means that a vessel which only has had short steaming periods pays the same way for each consumer as a vessel which was sailing all the time. Furthermore, a fundamental difference towards approaches based on actual operation is that such methodologies need to determine reference consumption figures for each operation mode, Fig.**2**middle).

Pool managers using methodologies, that work with a simulated operational profile, must define a reference draught and reference speed values to compare their fleets at the same operation points. Some Speed & Consumption model is required for these approaches.

3. Speed & Consumption methodologies

In principle, the vessel's sailing consumption depends on the vessel speed, the propulsion efficiency and the resistance. These values are impacted by many factors. In the following, three methodologies used by tanker pools to account for Speed & Consumption differences of vessels are described.

3.1 Average voyage performance profile

While the goal is to determine the fuel performance of a vessel at a simulated voyage profile and calculate TCE values (see 2.6), the first thing that comes to mind is to review the fuel performance of the actual voyages that she has sailed. Several pool managers have developed concepts based on the average performance of the conducted voyages from their vessel. The average fuel performance figures from the voyages of a vessel are determined and used to calculate the performance within the TCE profile.

A voyage is excluded or split if the vessel was sailing through bad weather, e.g. wind conditions above Beaufort 5. One only takes the "good weather days" and the calculated consumption figures are prorated for bad weather periods. Very short voyages below 24h or drifting times are not considered in such evaluation processes.

In case the entire voyage was in good weather, the pool manager determines the voyage performance figures by simple averaging:

$$Speed = \frac{VoyageDistance}{VoyagePeriod} \text{ and } Consumption \left[\frac{t}{24h}\right] = \frac{VoyageConsumption}{VoyagePeriod} \cdot 24h$$

The distance is taken from pilot station to pilot station, i.e. start of sea passage to end of sea passage. The voyage period is usually the difference between end of sea passage time stamp and start of sea passage time stamp, the main engine should have been running for the whole time.

After the pool manager has determined the average speed, rpm & consumption of each voyage, he can use this data to obtain the fuel consumptions at the common reference speed and draught. Some pools have developed performance models (e.g. based on sea trial) and calibrate those to the data. Others are using polynomials to extrapolate the values derived from the voyages. An example of the calibration step for a Ballast evaluation is shown in Fig.3.

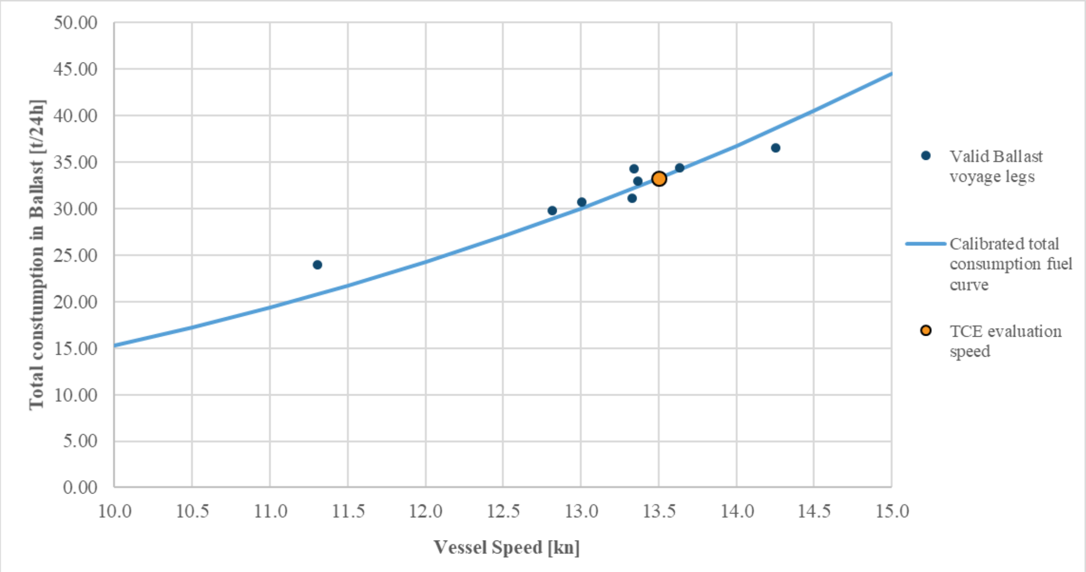


Fig.3: Consumption estimation based on voyages

Vessel speed changes over a voyage and by simple averaging one assumes a linear relationship between speed and fuel consumptions. Physically the relation is not linear, however in case the vessel voyage has had only a single main engine power, fuel consumption or rpm instruction, the fluctuations in speed are mostly due to environmental impacts and averaging leads to more or less feasible results. Still averaging gives wrong results when the instructions changed over the voyage, e.g. when the voyage charterer requests the pool manager to sail the vessel as fast as possible in the middle of the voyage. Such voyages need to be excluded as well.

3.2 Excess consumption compared to pool average

Instead of looking at the whole voyage one can also analyse the performance on a report level. The underlying idea of the excess consumption methodologies is to compare the fuel consumption of each report to the pool average consumption curve and reward or penalize for the difference. In the first step an average total consumption fuel curve for Laden and Ballast condition is created based on all valid and not excluded reports (e.g. blue curve in Fig.4). In the next step, the total reported fuel consumption of each valid report is compared to either the Ballast or the Laden average consumption value. The difference between the curve and the reported observation is the excess. Fig.4 shows an excess consumption which will have a negative impact on the Ballast evaluation of the vessel.

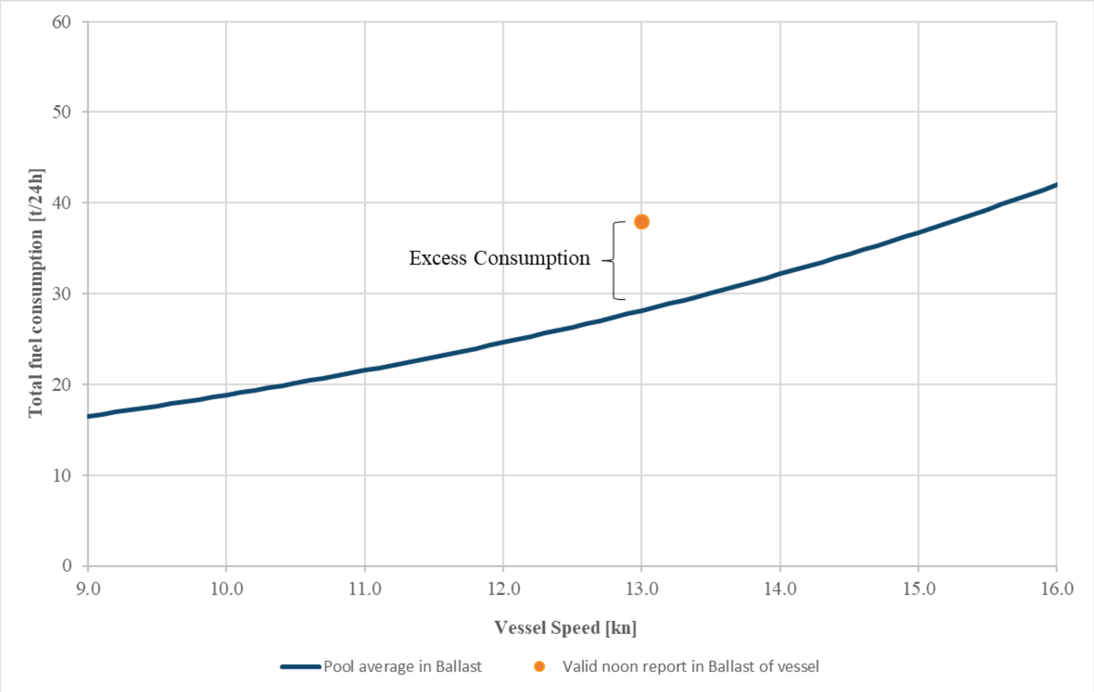


Fig.4: Actual vs. Pool average

Depending on whether the pool manager uses the actual or simulated operation patterns (see 2.6), he can either sum up the total excess over the evaluation period or determine an excess consumption percentage. So:

a. Actual Operation Profile of vessel:

$$TotalExcessCons[t] = \sum ExcessCons_{NoonValid} \cdot (1 + \%BadWeatherOperation)$$

It is assumed that the excess consumption for the valid observations can also be applied for the bad weather periods.

b. Simulated operation profile of vessel:

$$ExcessConsumption\% = \frac{1}{n} \cdot \sum \frac{Cons_{NoonValid}}{PoolAvgCons@Speed}$$

In a second step one multiplies the excess consumption percentage with the pool average value for the reference speed to obtain the sailing consumption in Ballast or Laden condition.

3.3. Methods using a hull & propeller performance indicator like ISO 19030

The methodologies described in 3.1 and 3.2 were using the total fuel consumption of each sea report or voyage leg from a vessel. By separating the consumptions related to main engine, the auxiliary engines- and the boiler one can use methodologies like ISO 19030 and review performance trends. Using the main engine fuel consumption means that the main engine- and the hull & propeller performance will still be analysed together.

ISO 19030 describes a standard methodology of hull and propeller performance assessments to analyze retrofit, maintenance and dry-docking effects using the average percentage of speed loss. Such approaches have been used by vessel performance analytics companies in the past decades to quantify the development of hull & propeller performance over time and between vessels. The methodology described in ISO 19030 was not developed to compare between vessels and focuses on high-frequency data, *ISO (2016)*. However, similar principles can be used when comparing vessels and with low-frequency data as well. Lloyd's Register recently certified the conformity Maersk Tankers proprietary methodology "Bunker Adjustment" with established methodologies and published international standards, including ISO 15016:2015 and ISO 19030:2016. So their concept seems to be similar to ISO 19030.

In the ISO19030 methodology one determines the performance indicator "percentage of speed loss" for each valid observation. Models correcting for the weather impacts are used. Additionally, reference models for the hull & propeller performance are required, which can be created, e.g. based on Sea Trial information. The percentage speed loss (V_d) is based on the reported and expected speed:

$$V_d = 100 \cdot \frac{V_{Reported} - V_{Expected}}{V_{Expected}}$$

To determine the average propulsion consumption for a vessel, one calculates in a first step the average performance indicator of all valid and not excluded reports in the assessment period. Fig.5 gives an example of how the average performance indicator is determined for a half yearly evaluation period.

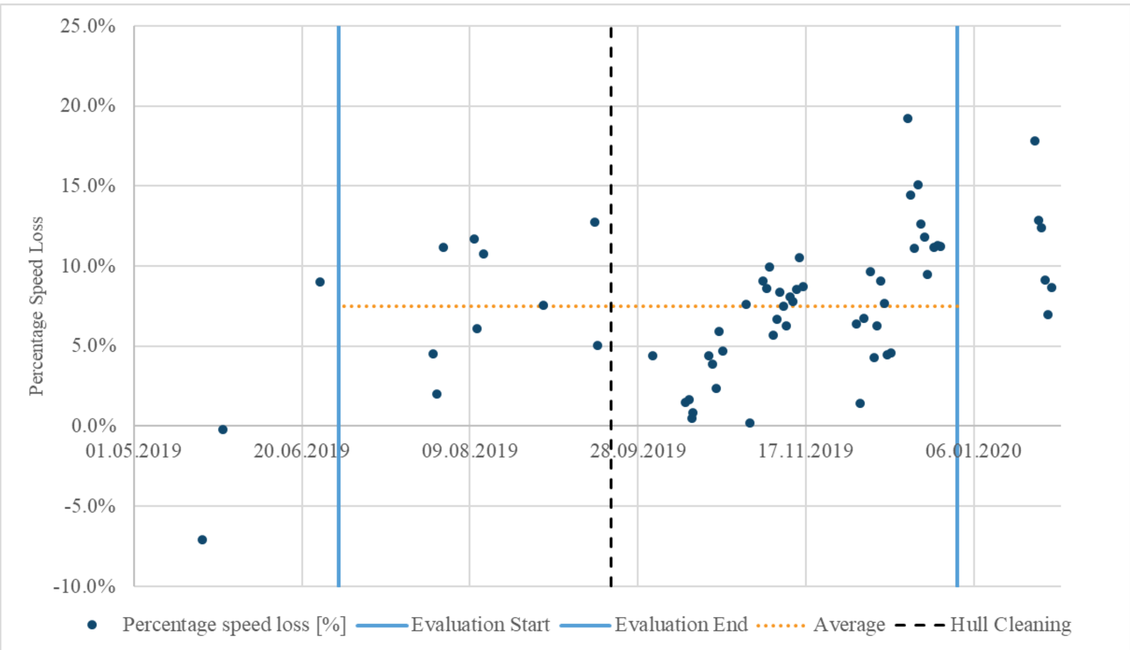


Fig.5: Percentage of speed loss – trend diagram

The average performance indicator of a vessel can then be applied to her hull & propeller performance model to back calculate the expected propulsion fuel consumption at the pool reference draughts (i.e. Ballast and Laden), speeds and weather conditions.

$$V_{d-average} = \frac{1}{n_{Valid}} \cdot \sum_{i=1}^{n_{Valid}} V_d \quad \Longrightarrow \quad PropulsionCons. = f(V_{d-average}, T, V, Beaufort)$$

In a pool evaluation process, further methodologies will be required to determine the average auxiliary engine and boiler consumption at Sea as well and derive the total Speed & Consumption figures for the reference sailing conditions.

4. Challenges within the process

Pool managers generally aim to have a pool point system in place that distributes the pool earnings in a fair manner between the pool partners. In the following a few challenges with the processes currently in place are highlighted.

4.1 Error by using daily averages & low frequency data

When a propulsion performance analysis is conducted for a group of vessels and using noon reports one can usually not trust that the speed logs of all vessels are calibrated correctly and that every vessel is equipped with a torsion meter at the propeller shaft. Hence one compares vessels at the simplest common denominators and for speed & consumption evaluations, one would be using the reported observed speed and the reported main engine fuel consumption.

Assuming above, the methodology described in Section 3.3 is similar to the ISO 19030–4, alternative approaches number 4. Excluding the effects of model uncertainties or possible human error, the ISO 19030-4 method is supposed to give with a 95% confidence interval an average error for a 6 months evaluation period of 4.57%, *ISO (2016)*. No thorough analysis regarding the accuracy of the other methodologies described in 3.1 and 3.2 could be found, but one can expect, that they give similar or worse accuracy levels.

4.2 Errors by the methodologies

Not all methodologies mentioned in Section 3 are estimating the fuel consumption values using physically correct approaches, as they are simply averaging the whole voyage speed or as they are not differentiating for draught differences beyond Ballast and Laden. Several methodologies use weather filters, but do not correct the valid observations for the weather impacts.

This is done by methodologies such as the ISO 19030 to compare the vessels within the fleet. However, such methodologies put a lot of trust in the models that are used as the performance indicator needs to be determined based on models. Hull & propeller performance models are often created with a certain amount of subjectivity (compare *Tsarsitalidis and Rossopoulos (2018)*) and the performance indicator can be speed or draught dependent and one should correct for this, *Schmode et al. (2018)*.

Pool managers using methodologies with simulated operation patterns can easily over- or underweight the fuel costs in their evaluation schemes. This happens when the simulated vessel operation differs from the trading patterns of the pool. E.g. when the manager evaluates all vessels at a reference speed of 14 kn, but the fleet average sailed speed was 11.5 kn, then the pool manager puts a higher weight on the fuel consumption than it has had based on the average operation. The reference speeds and draughts for simulated operation profiles should regularly be reviewed.

4.3 Errors through data manipulations

Most pools use only noon reports, which are manually entered by the crew. When reducing the consumption of a valid noon report by a few tons, this leads in general to an additional financial gain for the pool partner. Some pool partners may be tempted to instruct their crews to report lower consumption values at observations which are regarded as valid or to ensure that certain high consumption reports are not regarded as valid. Pool managers and vessel performance providers have limited capabilities to trace such behaviour.

4.4 Consideration of trading patterns

Certain trading patterns have a much higher likelihood of biofouling than others. However, the existing idle clauses of pool agreements allow the pool partners only under certain conditions to request an exemption and a hull cleaning. Also a few short idle periods in tropical waters can cause significant marine growth in particular when the antifouling is damaged through previous trading in ice or poorly executed hull cleanings. Most methodologies do not account for this circumstance and pool partners can be unlucky regarding where the pool managers are operating their vessels.

5. Summary

Pool managers have developed several methodologies to share the earnings among the pool partners with respect to their vessel's fuel performance and other factors. Due to this an event which impacts the fuel performance of a vessel significantly (like a dry docking, a hull cleaning or a retrofit) will generally result in higher vessel earnings within the pools.

The existing methodologies to determine Speed & Consumption differ significantly from each other and were often created with the goal to have a concept that people can easily understand from a commercial perspective. To determine the vessel's fuel performance is rather complex, as it is impacted by many different factors. This is one of several reasons why the accuracy levels of the described methodologies are limited.

Assuming that a methodology is able to assess the Speed & Consumption values with an accuracy level of about 95% for an evaluation period of half a year, the vessel is sailing for 50% and with average daily consumption of 22 t/24h, then this would result in an average evaluation error per vessel of:

$$AverageError = 0.05 \cdot 22 \frac{t}{24h} \cdot 0.5 \cdot 182.5 \approx 100 tons \left(@500 \frac{USD}{ton} = 50k\ USD\right)$$

The achieved accuracies of the methodologies that many pool managers use to determine Speed & Consumption have room for improvement. In general terms, the absolute uncertainty is reduced by either increasing the accuracy of the inputs and analysis functions or by increasing the amount of valid observations. Pool managers should focus on this.

Whereas every pool partner should have processes in place to regularly review the consumptions that the vessels are reporting and verify the correctness. The consumptions have an impact on the pool point equation and thereby a significant impact on the earnings of the vessel owner.

References

ISO (2016), *19030 - Ship and marine technology – Measurement of changes in hull and propeller performance – Part 1-3*, ISO, Geneva

NN (2016), *Special Report: Getting Smarter Through Pooling*, EURONAV

SCHMODE, D.; HYMPENDAHL, O.; GUNDERMANN, D. (2018), *Hull Performance Prediction beyond ISO 19030*, 3rd HullPIC, Redworth

TSARSITALIDIS, V.; ROSSOPOULOS, S. (2018), *ISO 19030 - The Good, the Bad and the Ugly*, 3rd HullPIC, Redworth

WARD, N. (2015), *Pooling agreements-an acceptable employment arrangement?*, Bryan Cave Leighton Paisner, https://www.bclplaw.com/en-US/thought-leadership/pooling-agreements-an-acceptable-employment-arrangement.html

Challenges in Ship Performance Monitoring and Methods to Overcome Them

Erik van Ballegooijen, VAF Instruments, Dordrecht/Netherlands, evballegooijen@vaf.nl
Torben Helsloot, VAF Instruments, Dordrecht/Netherlands, thelsloot@vaf.nl

Abstract

Estimating the deterioration of ship performance due to hull fouling and propeller roughness is a complex, multi-faceted problem. By collecting and interpreting full-scale sensor data the performance of the hull and propeller must be isolated from many other confounding influences. For this, expertise is needed in sensor technology, data collection, ship hydrodynamics, statistics and visualization. VAF Instruments is actively researching these topics in order to improve the accuracy of its performance monitoring solutions. This paper provides an overview regarding the importance of proper data collection, measuring speed through water, determining a baseline performance and visualizing results.

1. Introduction

Ship performance monitoring is a process in which the fuel efficiency of a ship is continuously observed. Through performance monitoring an operator is attentive to the efficiency of its ships and can quickly respond to those influences that threaten to undermine it. The operator can decide to have the hull cleaned when it has fouled, to have the propeller polished when it is rough, or to have it cleared when lines or netting has become entangled. Performance monitoring also helps decide whether to install a certain energy saving device, and if that decision was positive, it can help assess the effectiveness of said device. Within a fleet, high performers can be separated from low performers which will aid decisions regarding ship management. The more accurate and reliable the performance of ships is monitored, the better decisions can be made.

Performance monitoring thus provides many opportunities, but there are equally as many challenges. A large amount of variables are important to the fuel efficiency of a ship, and so a lot of information has to be collected from it. The fact that this information needs to be collected on board of a ship, in a harsh environment many miles out at sea, is a complicating factor. In addition, the crew of a seagoing ship has a great number of more pressing and important responsibilities than only collecting accurate data. This makes proper data collection an important challenge in performance monitoring.

It is an unfortunate fact that the physical quantity that is very important to performance monitoring, the ship's speed through water, is also difficult to measure accurately. An efficient ship needs a low amount of fuel to attain a high speed. This speed should be taken with respect to the surrounding water, on the grounds that an inefficient ship does not become suddenly efficient when it takes advantage of a tail current. More precisely, the speed that is of interest is the ground speed that would have been attained without any current. Because of the complex nature of the flow around a ship's hull, because of the current's own velocity profile and because of the difficulties inherent to the working principles of speed logs it is challenging to find out the 'true' speed and therefore 'true' efficiency of a ship.

In addition careful analysis is needed to separate those external influences that impact the fuel consumption from the fuel efficiency of the ship itself. The effect of wind speed, water temperature or waves, however interesting in and of itself, is not relevant when we attempt to monitor the performance of a ship in isolation.

Finally there is an additional challenge in communicating and visualizing the results. Information has to be presented in a way that is unsusceptible to misunderstanding. A visualization should not trick the eye into seeing spurious patterns and tendencies, nor bury real trends under an avalanche of datapoints. Moreover, it is important that the significance of uncertainty in the results is conveyed, so that a decisionmaker can take it into consideration. When a performance report lends itself to misinterpretation it might hamper decision making rather than help it.

The challenges in performance monitoring are plenty, but so are its advantages. Ship performance monitoring is a great tool to improve fuel efficiency. For this reason VAF Instruments has developed methods to address the challenges that were mentioned in this section. These methods will be discussed in the remainder of this paper.

2. Data collection

To measure the efficiency of a ship at the very least some measure of the energy input is needed. Either the fuel that sets the engine in motion, the shaft power that sets the propeller in motion, or the thrust that sets the hull in motion needs to be measured (see also Fig. 1 which shows the VAF Instruments combined thrust & torque sensor TT-Sense®). Preferably, all of the above. At the very least also the resulting speed of the ship needs to be measured. With this information the efficiency of the ship under any condition can be determined.

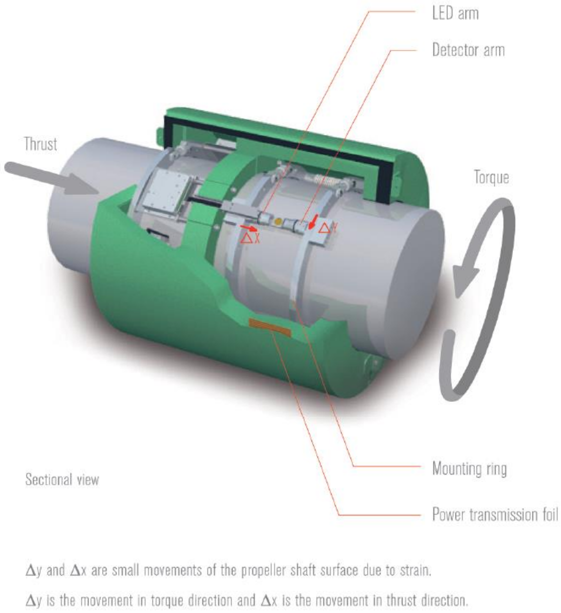


Fig.1: VAF Instruments TT-Sense® combined thrust & torque sensor

To be able to understand why the efficiency is as high or as low as it is, additional information is needed. It is important to know the draught and trim that the ship is sailing with, to know the weather conditions and to know the sea state. The temperature and depth of water is relevant to efficiency, and depending on the type of ship and area of operation the usage of stabilizers and the presence of ice may be relevant.

To collect all this information some ships are equipped with a great deal of sensors. On other ships only a minimal amount of sensors is installed, and the crew carries the burden to observe and report accurate information. Sensors on board of ships are always relatively delicate equipment in a relatively hostile environment. Quick repairs are often difficult, as the ship cannot be reached easily especially when it is out at sea.

VAF Instruments tries to overcome this challenge by designing its sensors but also the data collection systems to be as robust as possible. Consumer grade computers are not designed to survive for long on a ship, so it pays off to use an industrial PC to handle the data collection. Another strategy that works well is to build in redundancy. For example, a local back-up on the industrial PC mitigates data loss should the ship to shore communication fail. Redundancy is also desirable with regards to sensors. Many of our sensors store data locally so that historical data can be restored in case the connection to the data collection system breaks. Data may also be restored from alternative sources. For example, the output variables from global climate models serve as an alternative to the anemometer, the measurement of water temperature or weather observations by the crew. To some degree, missing information from draught sensors is made redundant by consulting the draught transmitted through AIS messages.

3. Speed through water

The measurement of speed on ships has historically been very important. Many years ago, the position of a ship could only be ascertained periodically whenever a star sight could be taken. In between star sightings navigation depended on dead reckoning, which required a sound knowledge of the vessel's heading and speed. The GPS has replaced this old system of navigation, and has therewith greatly diminished the need of knowing the ship speed. Ships nowadays have a speed log mostly because it is a SOLAS requirement, *SOLAS (2002)*.

For performance monitoring however, the speed log has become one of the most important devices of the ship. Large differences in fuel consumption lead to small differences in ship speed, so that a small error in speed measurement will lead to large errors in the performance analysis. It is interesting to note that there are now new developments in speed through water measurement motivated at least partly by this problem, e.g. *Gangeskar (2018)*.

Two types of speed log are currently most prevalent, one of them is the electromagnetic speed log. This type of device measures the flow speed of water in close vicinity to the hull, where the water flow is influenced by the hull itself. It will therefore have different measurement errors under different draft and trim conditions. The acoustic doppler log is also often used. This type of device is able to measure the velocity of the ship relative to thermocline layers several feet below the hull. At that distance the flow is less disturbed by the hull. However, the acoustic doppler log is known to be sensitive to variations in trim, and will for that reason also have different measurement errors under different loading conditions.

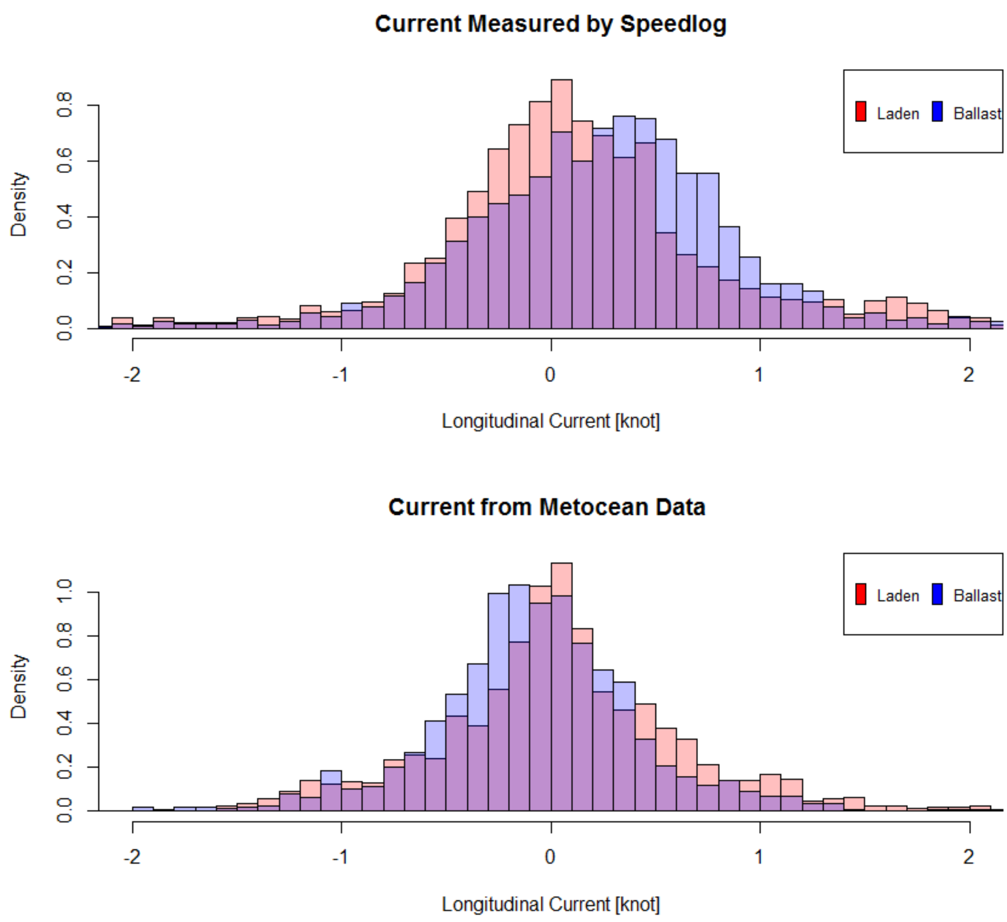


Fig.2: Speed log versus Metocean data

This leads to results such as in Fig.2. Displayed is the speed log data from a large tanker, sailing an intercontinental route alternating back and forth between laden and ballast with large differences in draught. The figure shows the head component of the current as measured by the difference between speed over ground (GPS) and speed through water (speed log), in comparison to the head component of the current predicted with the use of modelled ocean current data.

In the top half of the figure, the two translucent and overlapping histograms depict that in laden condition the current is centered around 0, whereas in ballast condition it is centered around 0.4 knots. It is possible that ballast trips truly have an average adverse current. However, the current as predicted from Metocean data does not confirm this. It is therefore more likely that the speed log has been calibrated for the laden condition, but has a bias whilst sailing in ballast.

The acoustic doppler log uses signals that travel through water with the speed of sound. However, the speed of sound through water varies with temperature. The temperature profile of the seawater can therefore have an influence on the quality of measurement of doppler logs. Fig.3 shows that, for a set of measurements taken during steady sailing conditions, the long term average of calculated current has a strong correlation with water temperature. These measurements were done on a cruise ship sailing in Asia, the Mediterranean and Northern Europe.

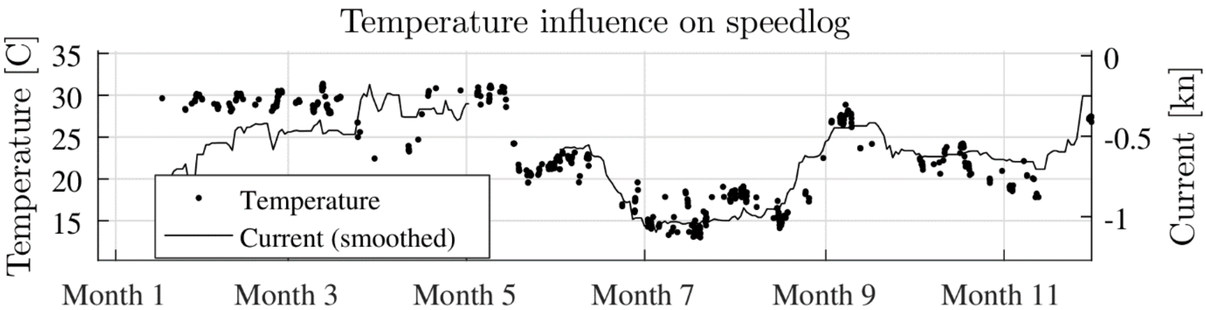


Fig.3: Smoothed (time averaged) calculated current versus water temperature measurements

From the preceding paragraphs can be concluded that changes in operating conditions and area will cause slowly varying changes in the error of a speed log. The corresponding errors in a performance analysis cannot be distinguished from the also slowly varying effects of hull fouling and propeller roughness.

To solve this problem VAF Instruments has developed methods to reduce the errors in speed log data by combining it with other sensor signals. Using the speed over ground instead of the speed through water is an option. Currents potentially induce large errors, but these will approximately average out in the long run. This means however, that data over a longer time span is needed before conclusions can be drawn. To improve on this, a recalibration of the speed log to match the speed over ground on average has been designed. This recalibrated signal captures the current variations in the short term, and reduces the long term variation in bias.

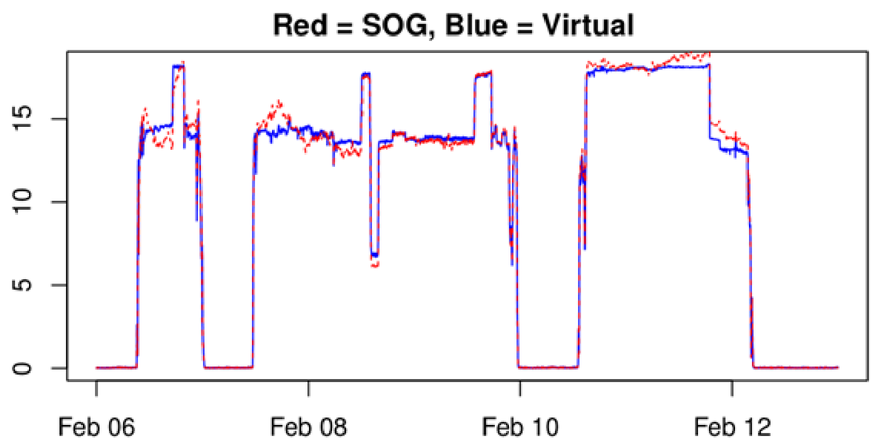


Fig.4: Virtual STW example

Another alternative to address the insufficient accuracy of the speed log is to create a virtual sensor that replaces it. Such a sensor estimates the speed through water by combining different sources of information. The virtual sensor, as described in *Ballegooijen et al. (2018)*, estimates the inflow velocity to the propeller using shaft rotation rate and propeller loading. It then estimates the relation between propeller inflow velocity and speed through water. Fig.4 shows an example of the results of this method.

4. Analysis

The goal of performance analysis is to track changes in ship performance resulting from things that are out of the ordinary, such as maintenance, repair and retrofit activities, *ISO19030-1 (2016)*. The goal is not to find out what the optimal sailing speed is, or the most efficient route to sail. Rather, the result of a performance analysis should depend as little as possible on operational and environmental parameters like speed, draught, wind and waves.

In order to achieve this, a reference level of performance is established for every condition. Those conditions for which such a reference cannot be created with sufficient accuracy are exempt from the analysis. In the ISO19030 standard it is recommended to do this using external information from model tests or computational fluid dynamics calculations, and possibly wind tunnel tests. In the discussion of alternative methods the standard also leaves room for the so-called ‘passive monitoring approach’, *ISO19030-3 (2016)*. For this approach all data that is needed is gathered during in-service operation and no additional steps need to be taken, which is a very attractive prospect in cases where it is difficult to obtain the necessary external information about a ship.

The challenge then becomes to distill out of the data a speed-power curve that would otherwise have come from a model test. A trained machine learning model might implicitly contain such a curve, or a more explicit statistical curve fitting method could produce it directly. In either case it is challenging to strike a balance between underfitting and overfitting the data. The suggested method in ISO19030 assumes a power law relation between speed and power, which is a good approximation for many ship types. However, in reality the relation is a bit more complicated, leading to situations such as the one illustrated in Fig.5 where the power law relation underpredicts in some speed ranges and overpredicts in others.

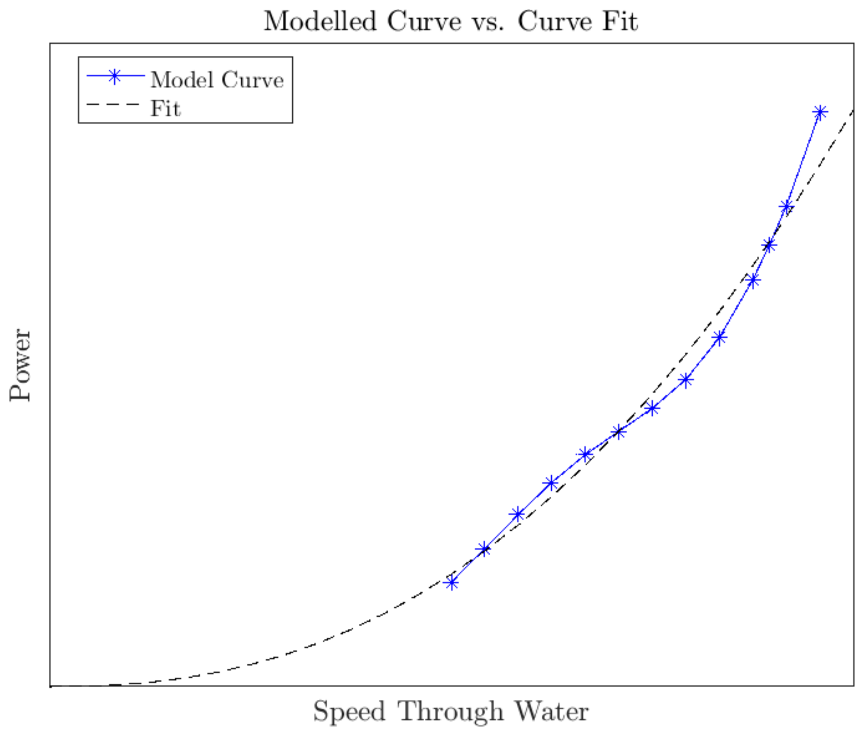


Fig.5: Real speed-power relation from model test versus power law curve fit

More free-form models than a power law relation have been found to be prone to overfitting. Overfitting is especially likely because typical passive monitoring data is heavily clustered, contains a mixture of additive and cumulative errors, and contains many different sources of error that vary in importance over time depending on the sailing conditions.

After a validated speed-power curve is in place, other parameters can much more easily be estimated from the data itself. Good results have been obtained with a curated speed-power curve in combination with purely data-based parameters estimating the influence of for example wind and stabilizer usage.

5. Presentation of results

The typical result of a performance analysis is a KPI with a certain variance and uncertainty. After the performance of a ship has been analyzed, the resulting information has to be conveyed to the end user. The end user typically makes decisions in response to the performance report, for which it is important that they know how to interpret the KPI's and understand the amount of uncertainty that is involved.

The same set of data can look very differently depending on how it is presented. This is especially true for someone who has not been involved in the data generation process. See for example Fig.6, where the upper plot puts a lot of emphasis on the outermost datapoints because they are most visible. The middle plot in the same figure puts more emphasis on parts where the data is most clustered, and the bottom plot shows only the mean of the data making it seem like a very constant signal. One could imagine drawing very different conclusions based on each of these plots.

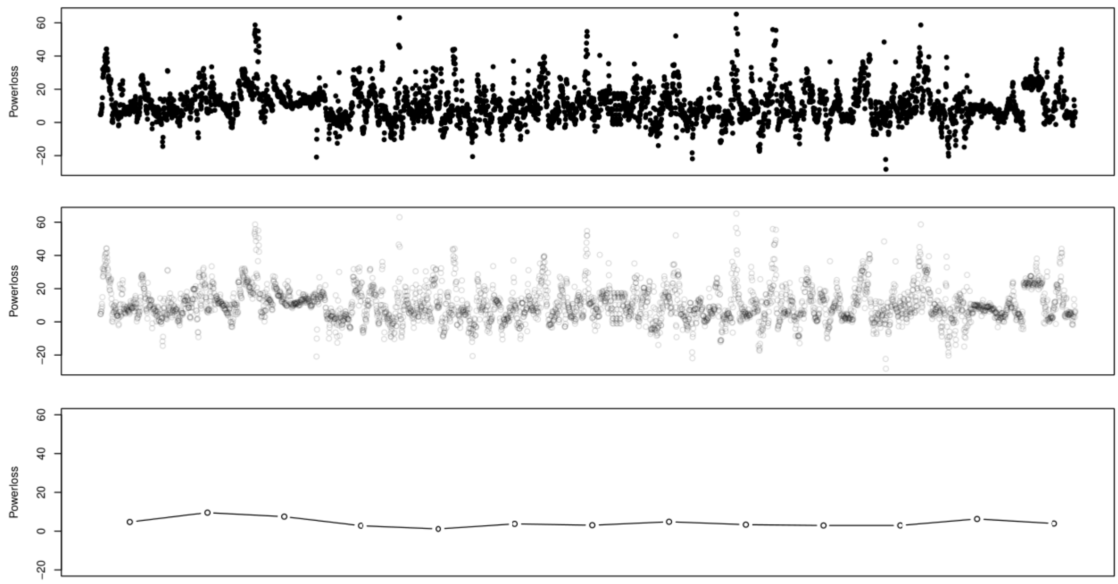


Fig.6: Different types of visualization

At VAF Instruments, effort has been put into making the performance analysis results intuitive to understand. KPI's were designed for the total loss of power, for power loss related to the hull and for power loss related to the propeller. These KPI's are very similar to the power performance value described in *ISO19030-2 (2016)* Annex K, here called power loss. The advantage of this is that power loss is easily converted to loss of fuel and costs, and that the KPI's for the hull, propeller and total can be easily related to each other because they have the same meaning. *Ballegooijen and Helsloot (2019)* describe this in more detail.

For the visualization scatterplots are no longer used, because from a scatterplot alone it might be difficult to see the central tendency of the data. However, only displaying a summary statistic hides the data distribution altogether, making the results seem much more definitive than they are in reality. For this reason a solution was chosen that tries to show both the central tendency and the variance of the data.

Fig.7 shows an example of the chosen visualization. Results are presented per month. Both the interquartile range and the average of the data are plotted, so that both the best estimate of the power loss and the variability of the underlying KPI values is visible. Steps in the power loss are shown at moments of maintenance, so that the effectiveness of cleanings can be easily judged.

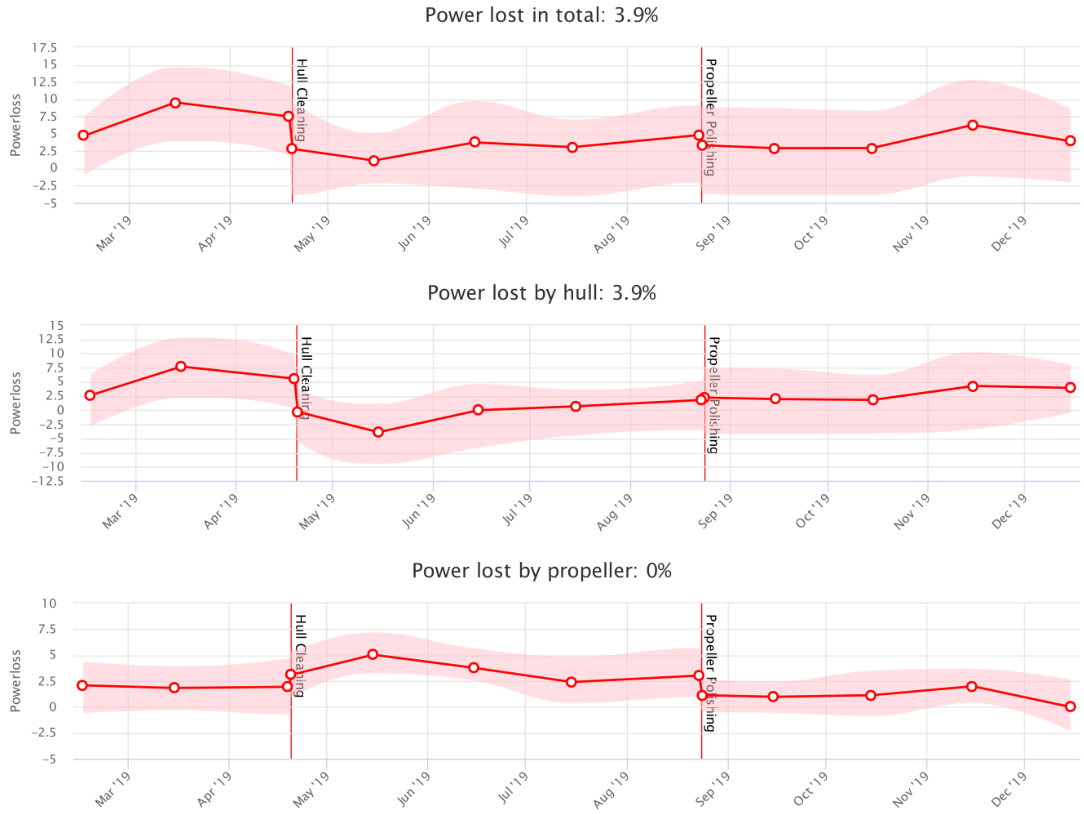


Fig.7: Performance report example

6. Conclusions

Ship performance monitoring is a valuable tool for increasing fuel efficiency. One of the prerequisites for it is reliable data collection via reliable sensors. To avoid downtime redundancy at several levels is helpful. At the sensor level by keeping data logs, at the data ingestion level by keeping local backups, and at the analysis level by having alternative data sources.

One of the most important data sources is the ship speed through water. To mitigate some problems with conventional speed logs two techniques were invented. One technique is to continuously reconcile the speed log data with speed over ground measurements. In this way a reduction of bias is achieved. Another technique to improve on the original speed log is to use a virtual sensor that estimates the speed through water via a combination of other sensor readings.

To monitor ship performance a performance reference is needed. When such a reference cannot be created because of a lack of external information about a ship, it can be based on full scale sensor data. This is referred to as the ‘passive monitoring approach’. To avoid overfitting, curves can be drawn up by a skilled professional instead of a computer algorithm. This approach has led to satisfactory results.

Once the results of a performance analysis are in, it is important that the information is effectively communicated towards the user. To this end, KPI’s were developed that are easy to interpret and a visualization is used that shows clear results without completely hiding uncertainty.

References

BALLEGOOIJEN, W.; HELSLOOT, T.; TIMMER, M. (2018), *The propeller as a speedlog: using full scale thrust measurements to quantify propeller efficiency and hull fouling*, RINA Full Scale Ship Performance, London

BALLEGOOIJEN, W.; HELSLOOT, T. (2019), *An approach to monitor the propeller separately from the hull*, HULLPIC 2019 Conf., Gubbio

GANGESKAR, R. (2018), *Verifying High-Accuracy Ocean Surface Current Measurements by X-Band Radar for Fixed and Moving Installations*, EEE Trans. Geosci. Remote Sens. 56/8, pp.4845-4855

ISO19030-1 (2016), *Ships and marine technology - Measurement of changes in hull and propeller Performance - Part 1: General principles*, ISO, Geneva

ISO19030-2 (2016), *Ships and marine technology - Measurement of changes in hull and propeller Performance - Part 2: Default method*, ISO, Geneva

ISO19030-3 (2016), *Ships and marine technology - Measurement of changes in hull and propeller Performance - Part 3: Alternative methods*, ISO, Geneva

SOLAS (2002), *Solas Chapter V "Safety of Navigation"*, International Maritime Organization, London, Regulation 19.2.3.4

Development of Performance Evaluation of Ships in Actual Seas
- OCTARVIA Project -

Masaru Tsujimoto, National Maritime Research Institute, Tokyo/Japan, m-tsuji@m.mpat.go.jp
Naoto Sogihara, National Maritime Research Institute, Tokyo/Japan, sogihara@m.mpat.go.jp
Hidehiko Sato, MTI Co. Ltd., Tokyo/Japan, hidehiko_sato@monohakobi.com
Kenichi Kume, National Maritime Research Institute, Tokyo/Japan, kume@m.mpat.go.jp
Hideo Orihara, Japan Marine United Corporation, Mie/Japan, orihara-hideo@jmuc.co.jp
Yoshihiko Sugimoto, Mitsui O.S.K. Lines Ltd., Tokyo/Japan, yoshihiko.sugimoto@molgroup.com
Mariko Kuroda, National Maritime Research Institute, Tokyo/Japan, kuroda@m.mpat.go.jp

Abstract

For the purpose of the establishment of the evaluation method for the ship performance in actual seas, OCTARVIA Project has started. OCTARVIA is a collaborative research project in Japan Maritime Cluster where 25 organizations including shipping companies, ship building companies, paint makers, ship machinery and equipment makers, classification society, research institute, and weather consulting company are participated. A new analysis method for monitoring data has been developed and the data filtering criteria become clear through the extensive validation. A reliable method for performance estimation in winds and waves has been developed which can be used at the design stage through the model tests and numerical simulations. Combined with these techniques, a program to evaluate the fuel consumption in the life cycle is proposed here.

1. Introduction

Global warming prevention is required internationally, and efforts are being made in each sector. In response greenhouse gas (GHG) emission from international shipping will further implemented and strengthened by regulations. In order to supply, operate, and maintain ships with low GHG emissions in actual operations, technology development is required.

Monitoring, Reporting and Verification by EU (EU-MRV), *EU (2015)*, and Data Collection System by IMO (DCS), *IMO (2016)*, start to report fuel consumption for ships. The data of EU-MRV reveals facts of 11,880 ships. However, the data is annual collection of figures including the effects of weather conditions, aging deterioration and so on. It remains questionable whether individual vessels can be evaluated based on these figures.

Efforts are also made to install monitoring devices on the ship and evaluate the operating status based on the acquired big data. The actual data can be easily evaluated anywhere.

In such a situation, ship operator has the following question; even if a lot of monitoring data are collected, they will not be led to performance comparison or evaluation. Ship designer has the following demand; in order to build a ship having good performance, it is necessary to develop a reliable performance estimation method which can be used at the design stage.

In Japan, a joint research project started to develop a method "a scale", to accurately evaluate the ship performance such as speed and fuel consumption in a sea area where waves and winds are actually acted on ships "ship performance in actual seas". In this paper, following *Sogihara et al. (2019)* the contents and development by the project are reported.

2. OCTARVIA Project

Project for Evaluation of Ship Performance in Actual Seas -Japan Maritime Cluster Collaborative Research- (OCTARVIA Project) has been carried out. The project period is three years from October 2017 to September 2020. The total budget is 660 million yen.

The purpose of OCTARVIA PROJECT is as follows; 1) development of a reliable estimation method for ship performance in actual seas and 2) establishment of a "Scale" which can objectively evaluate and compare the ship performance in the world with almost the same accuracy. Life cycle fuel consumption is selected as the scale and the target accuracy for the estimation method is selected as 2% of the main engine fuel consumption in actual seas.

2.1 Project Structure

Participants of the project are 25 companies from 8 (octo) sectors shown in Table I.

Table I: Participants of OCTARVIA Project

Sector	Company Name
Shipping company (3)	Kawasaki Kisen Kaisha, Ltd. Mitsui O.S.K. Lines, Ltd. NYK Line
Shipbuilding company (12)	Imabari Shipbuilding Co., Ltd. Japan Marine United Corporation Kawasaki Heavy Industries, Ltd. Mitsubishi Shipbuilding Co., Ltd. Mitsui E&S Shipbuilding Co., Ltd. Naikai Zosen Corporation Namura Shipbuilding Co., Ltd. Oshima Shipbuilding Co., Ltd. Sanoyas Shipbuilding Corporation Shin Kurushima Dockyard Co., Ltd. Sumitomo Heavy Industries Marine & Engineering Co., Ltd. Tsuneishi Shipbuilding Co., Ltd.
Paint maker (3)	Chugoku Marine Paints, Ltd. Kansai Paint Marine Co., Ltd. Nippon Paint Marine Coatings Co., Ltd.
Propeller & rudder maker (3)	Japan Hamworthy Co., Ltd. Kamome Propeller Co., Ltd. Nakashima Propeller Co., Ltd.
Governor maker (1)	Nabtesco Corporation
Weather consulting company (1)	Japan Weather Association
Research institute (1)	National Institute of Maritime, Port and Aviation Technology
Classification society (1)	Nippon Kaiji Kyokai

The project structures Project Management Conference, Steering Committee, Research Execution Body, Working Group and Research Team and Secretariat. The structures and members are shown in Fig.1. Each roll is as follows; 1) Project Management Conference receives report of research and budget, reviews them and decides matters specified by research participants, 2) Steering Committee considers the above upon receiving a referral, 3) Research Execution Body manages research according to the contract plan and makes coordination between Working Groups, 4) Working Group conducts research under Research Execution Body, 5) Research Team analyzes monitoring data for individual ships etc.

Three Working Groups (WG) are organized according to three sub-themes (S) as follows:

(S1) Establishment of ship performance monitoring method in actual seas
(S2) Establishment of estimation method of ship performance in actual seas
(S3) Establishment of evaluation of ship performance in actual seas.

Eleven Research Teams are established under S1-WG in consideration of the confidentiality of individual ships. The teams are shown in Table II. Object ships are many types of ship and cover large to small ships.

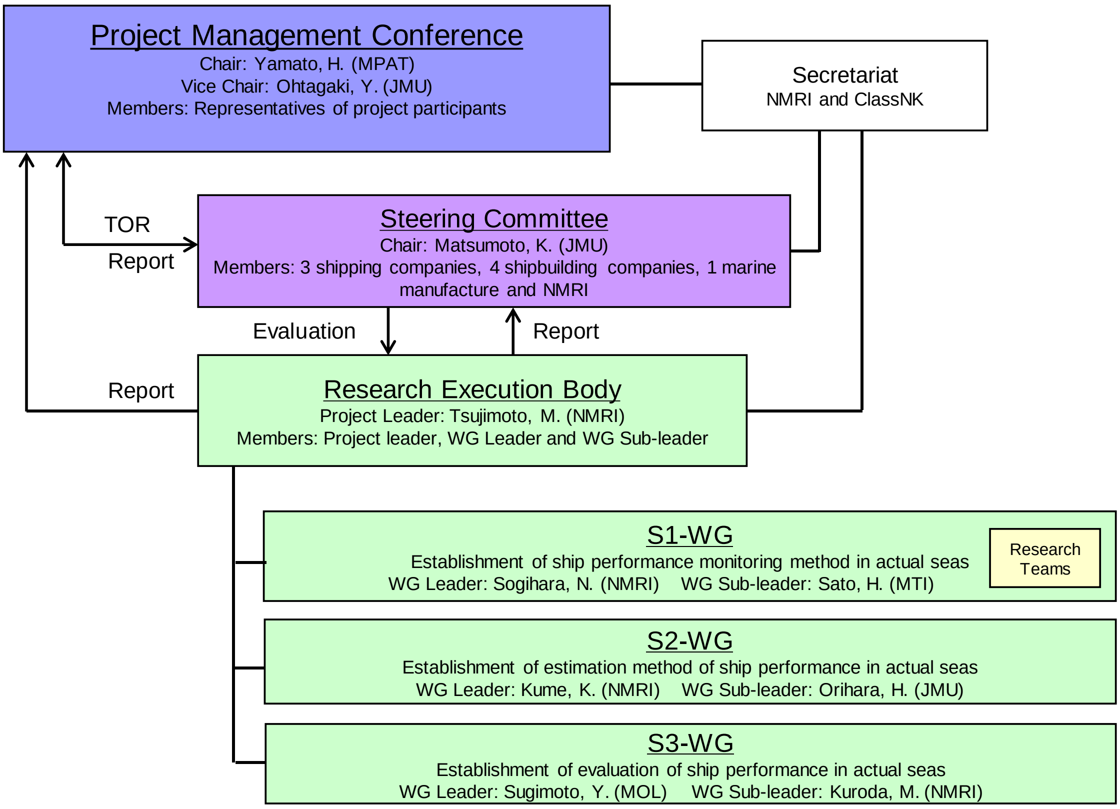


Fig.1: Project structure

Table II: Research Team and object ship

Ship type
Container ship (Panamax)
Container ship-A (over-Panamax)
Container ship-B (over-Panamax)
Ocean going PCC-A
Ocean going PCC-B
Mini-Cape size bulk carrier-A
Mini-Cape size bulk carrier-A
Very Large Ore Carrier (VLOC)
Tanker (MR)
Tanker (VLCC)
Training ship

3. Progress of WG

3.1 Monitoring Data Analysis (S1-WG)

ISO develops the standard for the measurement of changes in hull and propeller performance and its analysis, *ISO19030-2 (2016)*. The analysis method treats onboard monitoring data, however, disturbance correction of the data is applied to wind only. Wave correction was then considered in the future, as no appropriate method has been developed at the time.

A wave correction method applied in all directional waves is developed by International Towing Tank Conference (ITTC, 2017). The ITTC recommended procedures has been cited in EEDI survey and certification guidelines of IMO (IMO, 2018) and is used in EEDI verification.

S1-WG uses the method for wave correction to develop a rational and accurate method for analysis of monitoring data. As a result of examining the data filtering method, it is found that the use of apparent slip ratio can effectively remove unsteady data by manoeuvring and acceleration / deceleration.

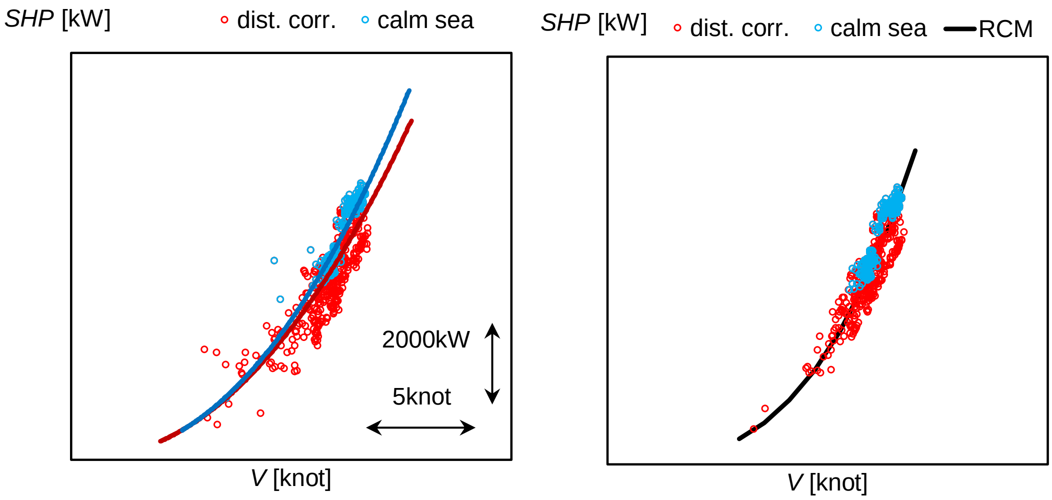


Fig.2 Fitting of speed (*V*)-power (*SHP*) curves (left: two fitting curves without RCM; right: using RCM)

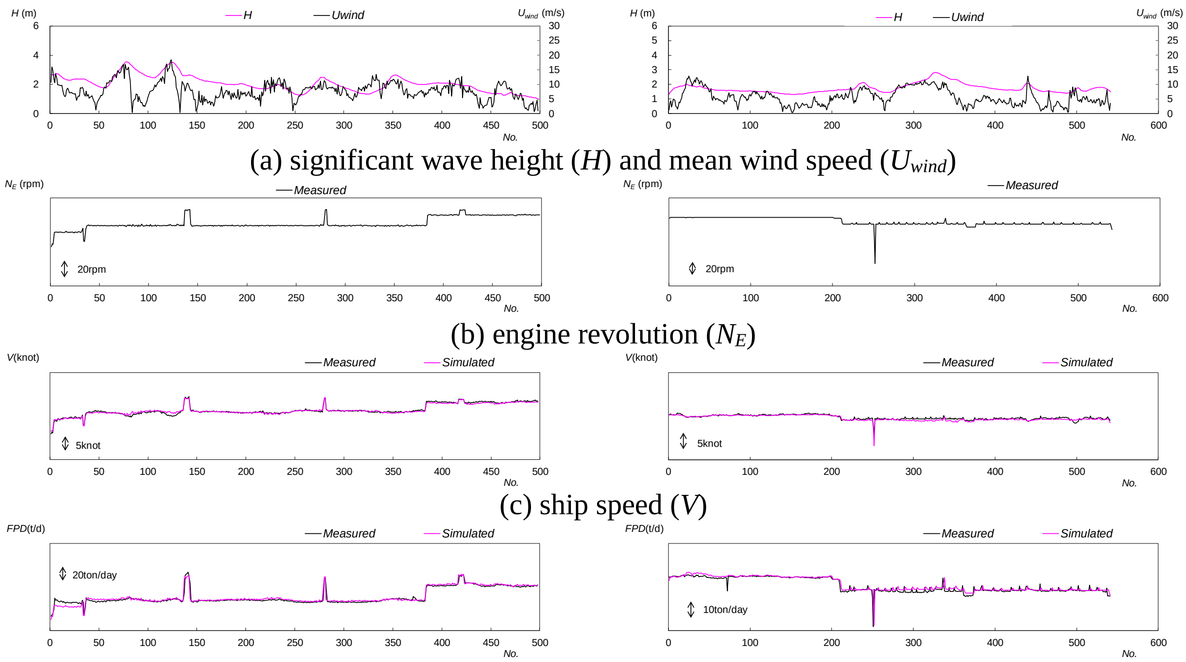


Fig. 3 Examples of simulation (left; Container ship (Panamax), right; Tanker (MR)).

Speed-power curve is effective to evaluate the quality of the corrected data. Accuracy of the correction for environmental condition affects the performance evaluation. For the quality control, it is better to use calm sea data, which needs small correction. However, after the data extraction close to the calm sea condition, it is sometimes difficult to draw fitting curve widely in speed range. This is because the data is concentrated on one point due to operating pattern. For this reason, this method also requires some idea. Therefore, a method, RCM; Resistance Criteria Method with apparent slip ratio and quality management), is developed using speed-power curve to compare the corrected data with data close to calm sea condition, and to have quality control information on whether they match well, *Sogihara et al.*

(2020). An example is shown in Fig.2, where "dist. corr." is disturbance corrected data, "calm sea" is extracted calm sea data with disturbance correction and "RCM" is the fitting curve obtained by RCM. It is found that RCM can obtain reasonable curve including low speed.

Table III: Evaluation of distance sailed (L_w) and total fuel consumption (*FOC*).

Ship	performance	percentage of difference
Container (Panamax)	L_w	-0.3%
	FOC	1.1%
Tanker (MR)	L_w	-1.7%
	FOC	2.0%

Using the RCM, performance simulations for ship speed (*V*) and fuel consumption per day (*FPD*) are carried out by the ship performance simulator (TSUJIMOTO et al., 2015). Fig.3 shows the examples of the simulations. Distance sailed (L_w), which is accumulated ship speed over time and total fuel consumption (*FOC*) for one voyage are evaluated. Table III shows percentage of difference between measured value and simulated result. From the comparison, it is found the method is enough accurate to evaluate ship performance in actual seas.

The calculation program "SALVIA-OCT." for analysis the monitoring data is under development shown in Fig.4. Currently, analysis method and the program are being verified using data from 11 ships.

To obtain accurate output through the disturbance correction, it is necessary to input ship hull geometry and ship performance. However, users do not always have such detailed information. In that case, a program for input support is prepared; "EAGLE-OCT.". In the program, hull geometry and ship performance are estimated using empirical formulas. It is applicable for " SALVIA-OCT.".

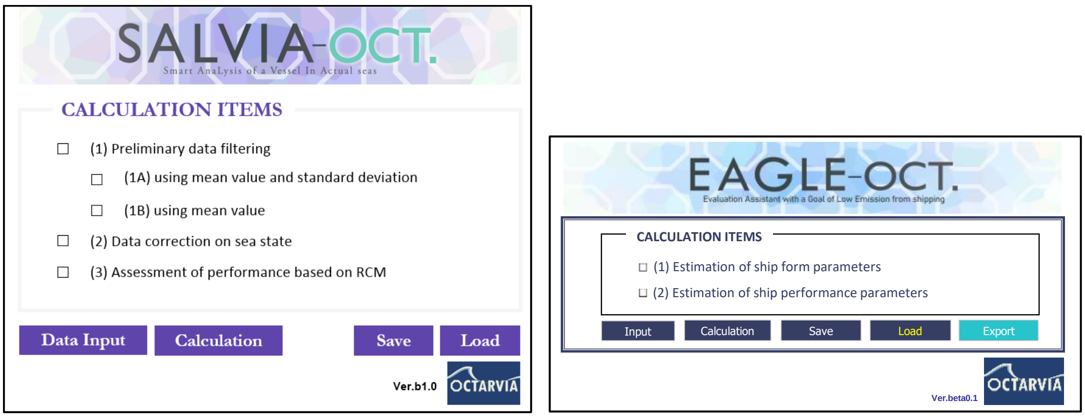


Fig.4: Program (left; SALVIA-OCT., right: EAGLE-OCT.).

3.2 Estimation of Ship Performance in Actual Seas (S2-WG)

S2-WG is developing a reliable estimation method of ship performance in actual seas at the design stage. At design stage, performance estimation is carried out by model tests and practical calculation method / CFD.

To evaluate ship performance in actual seas, estimation of resistance increase in actual seas and change of self propulsion factors in actual seas are important. Thus wind tunnel tests for 4 ships; a bulk carrier, a chemical tanker, a RoRo vehicle carrier and a container ship have been carried out. For the bulk carrier model, a round-robin test with 3 institutes was performed. Fig.5 shows arrangement of the wind tunnel test and the results of the round-robin test, *Kume et al. (2019)*. This work is proceeding in cooperation with ITTC. The recommended test procedures and analysis procedures will be developed.

Fig.6 shows pictures of the model test in waves using the same ship but performed in different tank. Through the round-robin tests in waves, the recommended test procedures and analysis procedures will be developed.

CFD calculation procedures should be standardized since the grid generation and convergence of calculation affect the calculation results. the numbers of tank tests, wind tunnel tests and CFD calculation are carried out. 12 companies share the CFD calculation in many parameters, *Kobayashi et al. (2019)*. The examples of CFD calculation are shown in Fig.7.

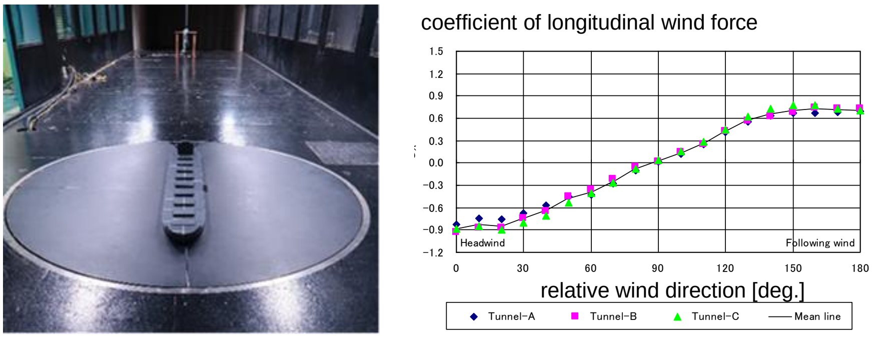


Fig.5: Evaluation of wind force (left; wind tunnel, right; result of round-robin test); (ψ; relative wind direction and C_X; longitudinal force coefficient).


Fig.6: Evaluation of self-propulsion factors in waves by a round-robin test

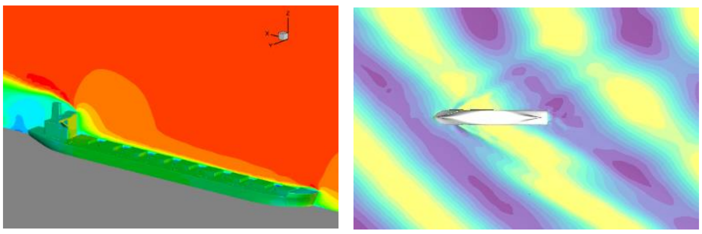


Fig.7: Evaluation of CFD (left: head wind; right: bow waves)

3.3 Evaluation of Ship Performance in Actual Seas (S3-WG)

S3-WG develops evaluation method of ship performance in actual seas. The index of ship performance in actual seas is selected as the life cycle fuel consumption.

In the calculation of the index, standard input items are set up. The input list is shown in Table IV. Six kind of the route can be selected with occurrence probability of weather condition on the route and season as shown in Fig.8. The occurrence probability is obtained by GLOBUS, which is the statistical database of winds and waves, *Tsujimoto et al. (2018)*. The database is published via the home page. Occurrence probability of weather on world-wide route is set up as north Atlantic weather designated by *IACS (2001)*, which provide severe probability of weather, which can be accepted in the world.

Occurrence probability of weather can be automatically calculated combining the routes and season as shown in Fig.9.

Output item (tentative) is shown in Table V. Predicted ship performance in actual seas is output to evaluate the ship performance. Fig.10 shows an example of ship speed and fuel consumption per day, where H is significant wave height. Time variation can be output. Fig.11 shows the decrease of the mean ship speed and increase of fuel consumption per day due to time progress considering aging deterioration and biological fouling.

This program allows you to evaluate the effect of reducing fuel consumption by changing the impact of fouling when the dock interval is changed.

A developed program is shown in Fig.12. The program is for index calculation and performance prediction; "OCTARVIA Index/Prediction".

Table IV: Standard input items

item	standard input
route	North Pacific West Pacific Asia-Europe via Suez Asia-Europe via Cape North Atlantic World-wide other
season	Annual Spring Summer Autumn Winter
input / selection	Direction of sailing (homeward/outward) Loading conditions Commanded Engine revolution Rate of operating days per year Rate of aging deterioration Rate of biological fouling Timing of cleaning (hull/propeller)

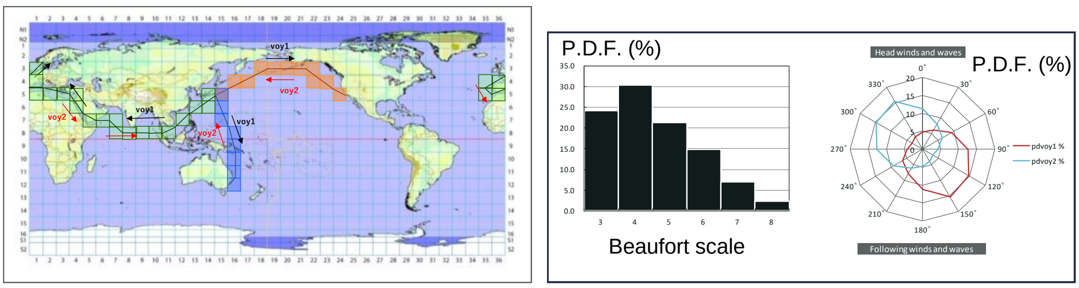


Fig.8: Route and occurrence probability of weather

	Rate for routes per season [%]					
Route	Spring	Summer	Autumn	Winter	r_{route} [%]	L_{route} [NM]
North Pacific	25	25			50	4900
West Pacific				25	25	4400
Asia-Europe via Suez			25		25	12200
Asia-Europe via Cape					0	15400
North Atlantic					0	4600
Total	25	25	25	25	100	
				Annual average		6600

Fig.9: Combination of multiple routes per season

Table V: Output item (tentative).

output item	unit
Life cycle fuel consumption	[ton]
Total amount of cargo	[ton]
Total distance for transport work	[NM]
Life cycle fuel consumption per day	[ton/day]
Fuel consumption per ton-mile	[g/(tonNM)

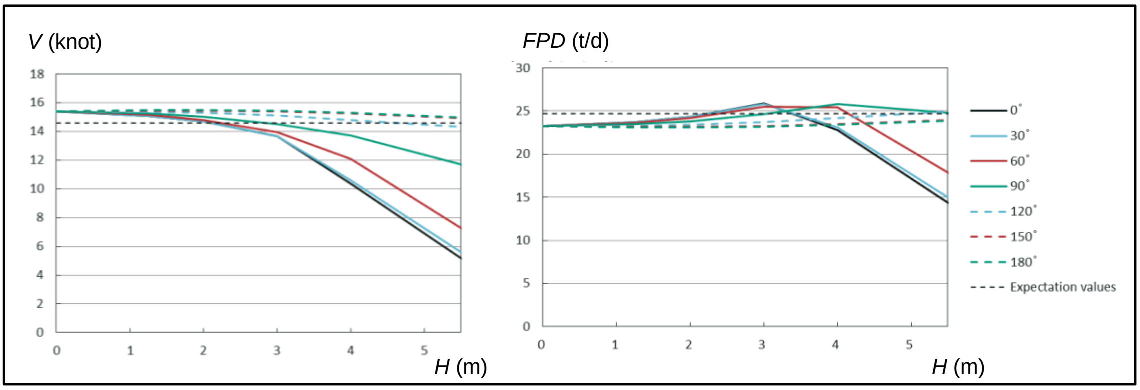
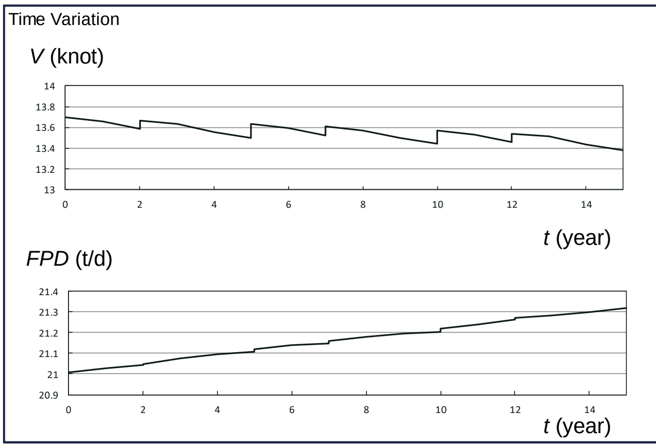


Fig.10: Predicted ship performance in actual seas (left: ship speed (V), right: fuel consumption per day (FPD) against significant wave height (H))



t	$V_{ave}(t)$	$FPD_{ave}(t)$	$FOC_t(t)$
year	knot	ton/day	ton
0	13.70	21.01	0.00
1	13.66	21.03	7682.61
2	13.59	21.04	15361.05
2	13.67	21.05	15361.05
3	13.64	21.07	23048.63
4	13.56	21.09	30754.91
5	13.50	21.11	38467.50
5	13.64	21.12	38467.50
6	13.60	21.14	46179.63
7	13.53	21.15	53897.20
7	13.61	21.16	53897.20
8	13.57	21.18	61634.57
9	13.50	21.19	69378.27
10	13.44	21.20	77115.87
10	13.57	21.22	77115.87
11	13.53	21.24	84864.53

Fig.11: Time variation and its list for ship speed (V), fuel consumption per day (FPD) and total fuel consumption (FOC); considering aging deterioration and biological fouling.

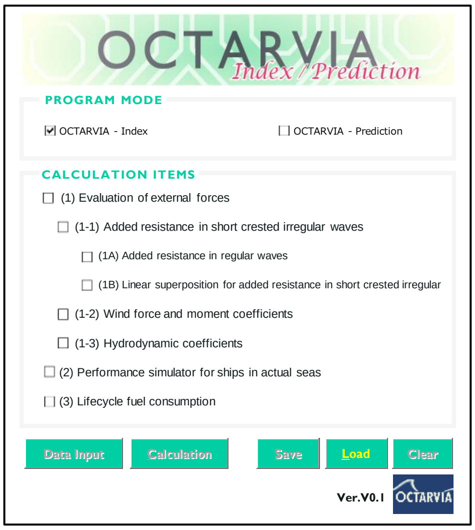


Fig.12: Program (Index calculation and Performance prediction)

4. Concluding Remarks

Digitalization is progressing in the maritime industries and onboard monitoring system is being implemented. It is considered that digitization, if used properly, can bring transparency and fairness. But it is not easy to draw out the right information to make a decision, since the big data contain uncertain factors such as weather conditions and manoeuvring operation.

The details of OCTARVIA project; (1) analysis of actual ship monitoring data by RCM and its accuracy, (2) initiatives of technical standards for model test and CFD calculation, and (3) life cycle fuel consumption as an index of evaluation of ship performance in actuals seas and its contents are presented. Activity of OCTARVIA project can accurately derive the ship performance in actual seas by properly processing the data using the naval architecture and ocean engineering. The features of the project are combination of three factors; (1) Monitoring, (2) Simulation, and (3) Evaluation & Judgment. Using the three factors, it is possible to correctly understand performance of a ship by handling big data.

Using the OCTARVIA index quantifies the impact of introducing high performance ships in actual seas, the impact of early docking on the hull cleaning, and so on. It brings benefits to stakeholders.

References

EU (2015), *Regulation (EU) 2015/757 of the European Parliament and of the Council of 29 April 2015, on the monitoring, reporting and verification of carbon dioxide emissions from maritime transport, and amending Directive 2009/16/EC*, European Union

IACS (2001), *Standard Wave Data*, Recommendation No. 34, Corr. 2001, International Association of Classification Societies

IMO (2016), *Resolution MEPC.278 (70), Amendments to the annex of the protocol of 1997 to amend the international convention for the prevention of pollution from ships, 1973, as modified by the protocol of 1978 relating thereto (Inclusion of regulations on energy efficiency for ships in MARPOL Annex VI)*, International Maritime Organization

IMO (2018), *Resolution MEPC.309 (73), Amendments to the 2014 Guidelines on Survey and Certification of the Energy Efficiency Design Index (EEDI) (Resolution MEPC.254(67), as amended by Resolution MEPC.261(68))*, International Maritime Organization

ISO19030-2 (2016), *Ships and marine technology -Measurement of changes in hull and propeller performance- Part 2: Default method*, International Organization for Standardization

ISO19030-3 (2016), *Ships and marine technology -Measurement of changes in hull and propeller performance- Part 3: Alternative methods*, International Organization for Standardization

ITTC (2017), *Recommended Procedures and Guidelines 7.5-04-01-01.1, Preparation, Conduct and Analysis of Speed/Power Trials*, International Towing Tank Conference

KOBAYASHI, H.; KUME, K.; ORIHARA, H.; IKEBUCHI, T.; AOKI, I.; YOSHIDA, R.; YOSHIDA, H.; RYU, T.; ARAI, Y.; KATAGIRI, K.; IKEDA, S.; YAMANAKA, S.; AKIBAYASHI, H.; MIZOKAMI, S. (2019), *Suitable computational conditions for computing added resistance in head waves - based on parametric study by RANS simulations* - (in Japanese), Proc. Japan Society of Naval Architects and Ocean Engineers 29, pp.205-208

KUME, K.; OHBA, H.; ORIHARA, H.; MIZOKAMI, S. (2019), *Wind Velocity Profile and Representative Wind Velocity for Wind Resistance Measurement of Ship Models*, J. Japan Society of Naval Architects and Ocean Engineers 30, pp.1-13

SOGIHARA, N.; YONEZAWA, T.; ISHIGURO, T.; SUGIMOTO, Y.; MASUYAMA, S.; MIENO, H.; SHIMADA, M.; MATSUBARA, Y. (2019), *Introduction of OCTARVIA Project: Project for Ship Performance in Actual Seas*, 4th Hull Performance & Insight Conference, Gubbio, pp.21-30

SOGIHARA, N.; SAKURADA, A.; TSUJIMOTO M.; SATO, H. (2020), *Validation of the Evaluation Method of Ship Performance Using Onboard Monitoring Data -Development of Resistance Criteria Method with Apparent Slip Ratio and Quality Management*-, 5th Hull Performance & Insight Conference, Tullamore

TSUJIMOTO, M.; SOGIHARA, N.; KURODA, M.; SAKURADA, A. (2015), *Development of a ship performance simulator in actual seas*, 34th Int. Conf. Ocean, Offshore and Arctic Engineering, OMAE2015-41708

TSUJIMOTO, M.; MATSUZAWA, T.; KUME, K. (2018), *Statistical Characteristics of Global Winds and Waves*, 28th Int. Ocean and Polar Engineering Conf., pp.379-386
https://www.nmri.go.jp/study/Intellectual/globus/namikaze_main_e.html

Bridging the Gap Between Noon Data and Automated Data

Jóan Petur Petersen, GreenSteam, Lyngby/Denmark, jpp@greensteam.com
Jonas S. Frederiksen, GreenSteam, Lyngby/Denmark, jsf@greensteam.com
Daniel J. Jacobsen, GreenSteam, Lyngby/Denmark, dj@greensteam.com

Abstract

This paper looks at how much ship performance modelling can be improved by collecting one or two high-frequency signals onboard: fuel flow, or fuel flow and RPM. This is done by comparing the predictive performance of similar models on noon frequency and higher-frequency data. The results show that with very little extra hardware onboard, the modelling can improve considerably.

1. Introduction

It is considered good practice for a ship to record their daily fuel consumption in the engine logbook and noon report. These data are often used for creating various performance measures, which are used to monitor and optimize the performance of the vessel. Noon reported fuel consumption is still the only data collection on many vessels today, and due to its low temporal resolution, manual nature, and use of local time it is worth questioning how accurate the results based on these data are.

In this study, we will look closer at the fuel and RPM readings stored in the engine logs for a vessel and quantify how well it can be used to estimate the propulsion efficiency compared with higher frequency automatically logged fuel and RPM data. Even though we only look at one vessel, these findings should generalize for other vessels too.

2. Data

The most crucial data for propulsion modelling from the engine logbook or noon report is, in most cases, the fuel consumption, RPM, and draft of the vessel. Most other information in the noon report is available from other sources online today. Weather information about wind, waves, and currents can be obtained online from metrological services, and the speed over ground and distance traveled by the vessel can be obtained from services that collect AIS data over terrestrial and satellite systems. Draft is also available as part of the AIS data, but these are often unreliable, as they are entered manually, see *Jia et al. (2019)*. Unless some cleaning and validation of the AIS draft is done, it cannot be used in general.

The data we use is collected onboard a ship, which we will keep anonymous. We obtain the fuel consumption and main engine RPM for the vessel from two sources: the engine logs and from an automatic data collection system onboard. The automatic data collection system stores average fuel consumption and main engine RPM every 10 minutes. The average is based upon the last 10 minutes. The data spans one year.

The ship has a flow meter installed, which measures the total fuel flow to the main engine. The ship does not have any shaft generators, so all the fuel is used for propulsion. The crew does the manual fuel readings from a display on the flow meter, which shows the accumulated flow. The counter gives the total number of liters passed through it. The crew can reset the counter, but this happens rarely. The consumption since the last noon report will be the difference in the counter value unless the crew has reset the counter. In the case of the meter being reset, we have to assume that it was reset just after the last reading, and the new value is the consumption since the last noon report. It is an advantage that the crew is reading accumulated fuel flow values, as this will tend to make the readings correct over longer periods. In the cases where the ship does not have fuel flow meters, tank soundings or similar will be used to measure the daily fuel consumption, and this will introduce more uncertainties. The main engine RPM is also accumulated on a display and works in a similar fashion to the fuel meter.

Noon reports and engine logs are reported each day at noon in ship's time. We will assume that the ship uses nautical time and switches time-zone at midnight. The nautical zone-time system was introduced in June 1917 at an Anglo-French Conference on Time-Keeping at sea, *Howse (1980)*. Clock changes required by changes in longitude, preferably in one-hour steps. One hour corresponds to 15° in longitude, and the zero-offset time-zone runs from 7°30′W to 7°30′E. However, in practice, it is the Captain who decides which time is used onboard, and when the clock is moved between time-zones. Because the noon data is collected in onboard ship time it introduces some problems. If the ship crosses a time-zone, the length of the day will change plus or minus one hour, except when it crosses the International Date Line, then the ship moves between time-zone offsets +/- 12 hours, and the noon report date might appear twice, or a date might be missing depending on which way the ship is sailing. We must take care to handle this consistently in the conversion, and later processing. The engine logs do not show the length of the day but state the main engine running time, and from that, it is evident that they use local time, as the running hours are mostly 24 hours, but then sometimes 23 and 25 hours, see Fig.1.

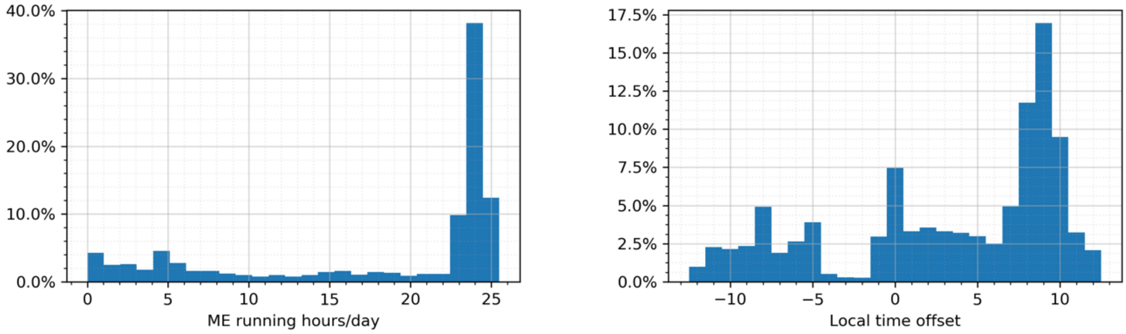


Fig.1: Left plot gives the ME running time reported in the engine log. Right plot the UTC offset for the ship's time based on ships position from AIS.

The engine logs give the time of the reading, but it is almost always 12:00 ship time in this case; only eight times it is reported not being at noon and they all appear around the same time. If the readings are not done at noon, this will shift the corresponding fuel consumption or RPM between the adjacent days of the noon report, resulting in one being overvalued and the other undervalued.

There are 4 dates missing in the noon report, but here the ship is berthing or anchoring. Three dates are skipped due to the International Date Line. There are 16 dates where a noon report appears more than once per day. Some have been marked in different ways as faulty: colored text or background. This illustrates the problem with manually handling data in a spreadsheet, as there might be small variations in consistency, which requires more manual work afterwards. Data validation can be built into the spread sheet alleviate this.

For this study, we will use local time onboard as a reference. We will find the time-zone used onboard from the high-frequency position obtained from AIS data and map all the data into the ship's local time. Having the mapping one would also be able to map the other way, if one would like to work in UTC, however, the days from the low-frequency reports would not line up with the UTC days. Working in ship time is also problematic, as the days will not be uniquely identifiable by the date alone. We have not done anything with this problem here, as there are so few dates that appear more than twice, so we have left them as 48 hours days, which will result in a higher than usual fuel consumption for these.

Fig.2 illustrates how well the manual and automatic data agree. The Pearsons correlation coefficient is 0.87 for the fuel, and 0.90 for the RPM. For the fuel signal most of the points lie close to the unity line, however there are a few points that have gone astray: there are a few points where the automatic system's readings are very low compared to the manual readings. Variations in the time of reading and signal noise could explain some of the variations around the unity line. However, these points are too far away from the unity to be explained by this. Looking closer at the speed and the fuel consumption of the vessel, we have found that the automatic fuel readings are sometimes zero when the ship is sailing. This seems to happen mostly at the start of the dataset's period. We do not know if the automatic fuel measurements are always zero when it fails, or it could be some other wrong value. Nevertheless, we have the manual reading to confirm that they are reasonable most of the time.

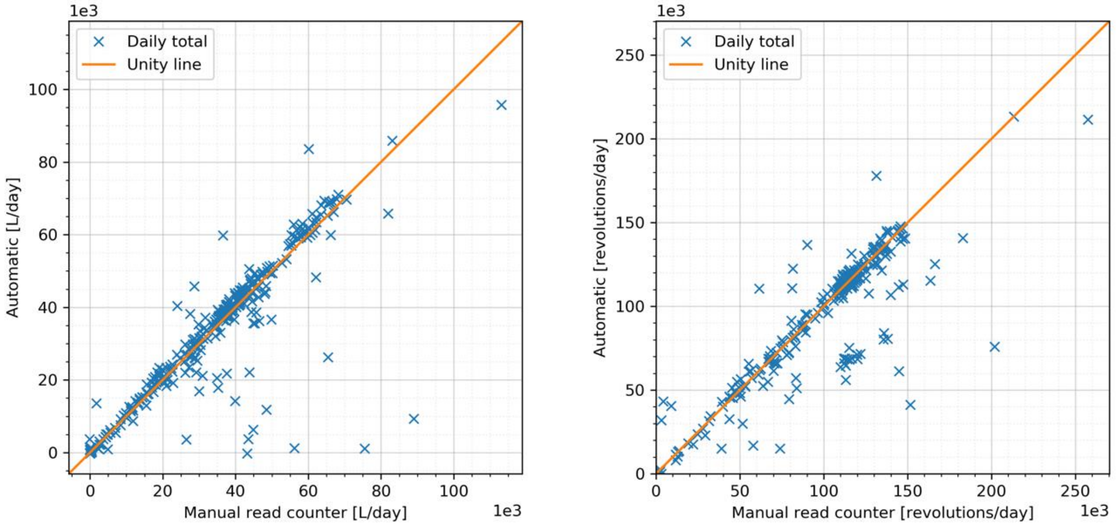


Fig.2: Manual noon report readings versus automatic readings noon to noon onboard. Left plot gives the fuel consumption, and the right the main engine revolutions/day.

Going back to Fig.2, we can see that the fuel points might tend to be located over the unity line, meaning that the automatic readings tend to be a bit higher than the manual. The data is transmitted between the flowmeter and the data collection system using a 4-20 mA signal, and a calibration error in this setup could result in such an error. Transmitting the data digitally instead could maybe have solved this problem and would be preferable. The RPM signal collected automatically is transmitted digitally using NMEA.

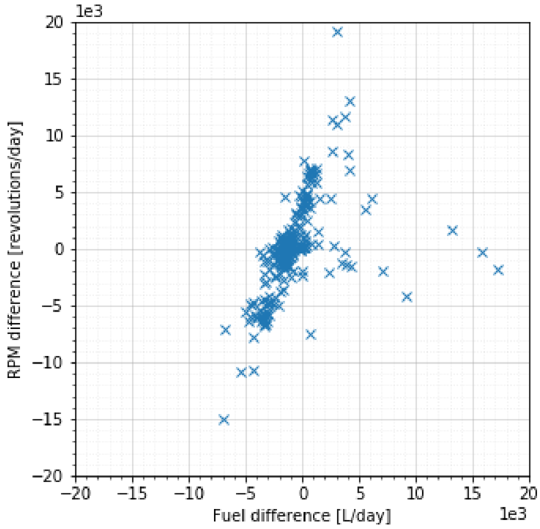


Fig.3: Relation between fuel and RPM differences in manual and automatic measurements

In Fig.3 we see that there is a positive correlation between the differences in the manual and automatic readings. The difference is calculated as the manual minus the automatic. Because the fuel and RPM are measured by two independent systems, it could indicate that this correlation has something to do with the manual readings. It could be related to the time-zone switches and to variations in the times of the manual readings.

3. Methods

We will use an Artificial Neural Network (ANN) to investigate how well the relationship between fuel consumption, RPM, and other variables can be explained by the two different types of data: low- and high-frequency. We will use the same inputs for both the low- and high-frequency data sets to compare them fairly. In reality, models based on data from high-frequency automatic data collection systems often use more inputs and can have better performance than what we will see here. However, the goal here is not to get the absolutely best performance, but to compare the performance obtained from low- and high-frequency datasets.

Using an ANN regression model to capture the relation between the signals seems like a good way of benchmarking the signals because as pointed out by *Aldous et al. (2013)*, there is no authoritative reference benchmark. We have selected these additional inputs: the speed over ground from AIS data, transversal and longitudinal wind approximated by course, wave height from weather services, the draft from the automatic data collection system, and finally the sea depth from a depth chart. We will also generate a STW signal based on historical metrological sea current data, which we will use instead of the ground speed to investigate what influence it has. This dataset has been inspired by data used by the ISO 19030. As mentioned earlier, this data is available online, except for the draft. Here we assume that the departure drafts have been collected by the crew and simulate this using the data from the automatic system. However, in reality, crew submitted drafts would also introduce new errors. For the low-frequency data set, the drafts have been set to the beginning of each voyage. The low-frequency model will in addition to this get the number of hours in the day, which is inherent in the summation done with the high-frequency model. We have not done any special data cleaning, except that the entries with problematic fuel data have been removed, where the fuel consumption was zero when the ship was sailing.

We have selected the fuel consumption as the target value to be predicted, so the rest of the signals will be used as inputs. Data is divided up into a training and a test set, 50/50. Samples are distributed randomly between the sets on a day resolution, also for the high-frequency dataset. The test set is not used for anything else than evaluating the result at the end. The training set is used to generate 10 Artificial Neural Networks using early stopping as regularization. A part of the training set is used to determine when to stop training. The average of the output from the 10 models is used as the result of the low-frequency model. For the high-frequency model, the sum over the day for the average from the 10 model outputs is used.

4. Results and discussion

The results are given in Table I. To quantify the error, we will use the Normalized Root Mean Square Error (NRMSE), where we take the root mean square error and divide it by mean of the target values. The manual column gives the results where we use the manually collected fuel and RPM. The Noon Automatic column is similar to the first column, but now using automatically collected fuel and RPM as daily averages instead of the manually collected. Finally, the Automatic column gives the results for the high-frequency automatic data.

Table I: Training set and test set performance for model setups

		Manual		**Noon Automatic**		**Automatic**	
		Train	**Test**	**Train**	**Test**	**Train**	**Test**
Using SOG	**With RPM**	21.1%	22.8%	15.8%	19.8%	2.0%	8.6%
	Without RPM	26.6%	33.8%	17.6%	24.9%	7.0%	14.9%
Using STW	**With RPM**	19.0%	23.7%	14.7%	16.5%	1.9%	4.9%
	Without RPM	24.1%	31.3%	14.4%	18.4%	5.3%	9.4%

The purpose of having the Noon Automatic column, is to identify the impact of manually storing the values. The difference between the Noon Automatic and the Automatic results are mostly due to the sampling frequency, but the Manual results also include the human factor. We have trained the models with and without the RPM signal. If one were to only select one signal to collect onboard, one would probably go with the fuel consumption first. The performance for the automatic setup without the RPM performance outperforms all the low-frequency setups. As one would expect the model using high-frequency fuel and RPM has the best performance.

There are simple and inexpensive data loggers on the market today; at the time of writing, some cost around €200 that can collect 4-20 mA signals with time stamps, and run on batteries for many years reducing the wiring needed. We would recommend that if the ship has a fuel flow meter, then the fuel consumption is collected at least using such a simple and cost-effective device. If the vessel does not have fuel flow meters, then the cost will be higher, and dependent on the setup onboard. With a simple data collection system, we would have the advantage of having the automatic continuous measurements in UTC at a higher frequency and higher consistency. Fig,4 illustrates how well the low-frequency model can predict the fuel consumption.

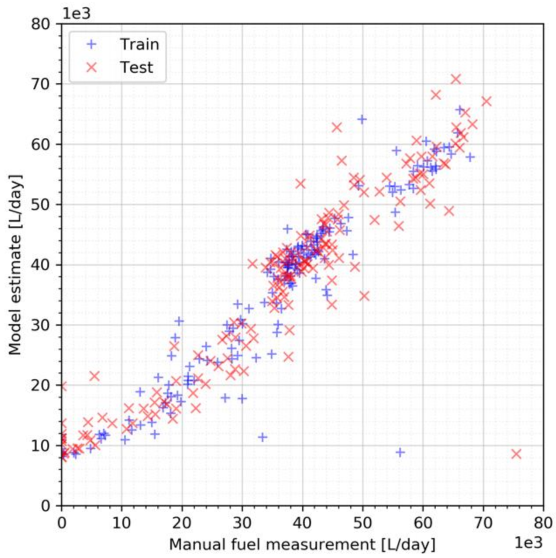


Fig 4: Predictions by low-frequency model for the training and test sets using RPM and SOG

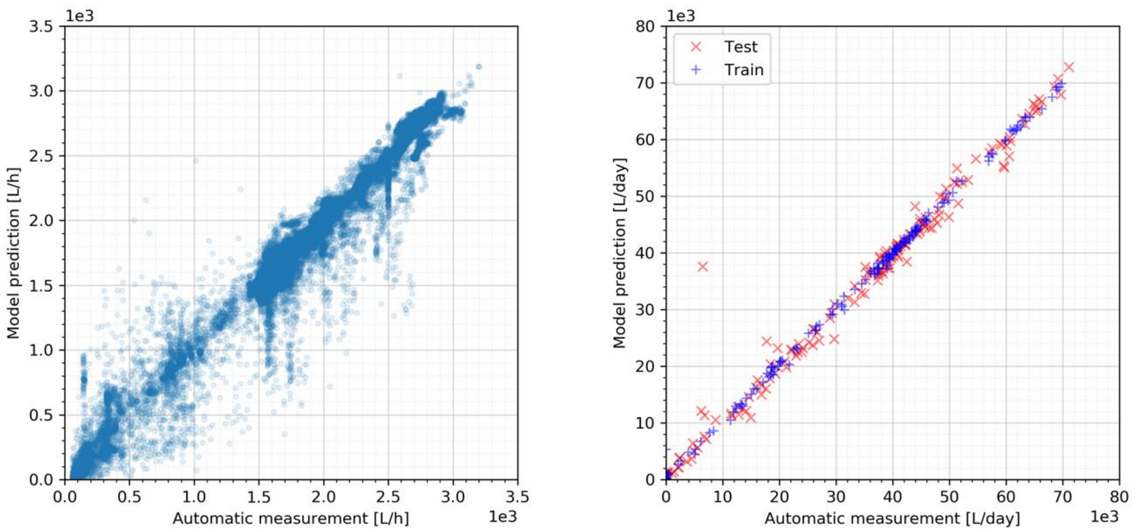


Fig 5. The plot on the left shows the high-frequency predictions on the training set each high-frequency sample. The plot to the right gives the training and test samples prediction sums for the whole day. Both using RPM and SOG as an input.

Fig.5 visualizes how the high-frequency model can describe the data. Even though the noise is high for each 10-minute sample, the predictions have a low bias error, which results in good daily predictions. This high-frequency model does not seem to have similar problems with predicting the higher fuel consumption, and generally, the noise is less than for the low-frequency data set.

The reason for the better performance of the high-frequency model is most likely that the low-frequency sampling rate is too low to capture essential information sufficiently. Changes in the speed and other important signals during the day will not be captured by the low-frequency model.

5. Conclusions

Based on the findings in this article, it is clear that high-frequency data is better suited for modelling the performance of the vessel, and that the manual collection process itself introduces additional errors that lead to a further significant drop in prediction accuracy. However, noon data could still be useful for detecting problems in the automatic measurements, as we have seen here. By comparing the noon data with the automatic data, we discovered that the automatic system occasionally drops out, and that there are some calibration issues with the analog transmission of the values. Another advantage is that the noon data also adds redundancy to the fuel measurements, which could be helpful if the automated system fails.

We have seen that one of the drawbacks of the noon data is that it uses the ship's time, which could lead to uncertainties about how to align it to UTC and what procedures the ship uses when changing time-zones, and then there are the potential human errors.

The results from this vessel show that, the model based on the higher frequency data is considerably better at predicting the total daily fuel consumption. It is clear that just by storing the fuel consumption using an automatic collection system, the data becomes significantly better for modeling the propulsion efficiency of the vessel. Collecting data onboard does not have to imply costly installations in some cases, as we have discussed, and we would recommend collecting the data automatically onboard.

References

ALDOUS, L.; SMITH, T.; BUCKNALL, R. (2013), *Noon report data uncertainty*, Low Carbon Shipping Conf.

ASHIDA, T.; MIZUTANI, N.; PAKKANEN, P.; VÄISÄNEN, A.; MANDERBACKA, T. (2019), *Performance Monitoring Insight at MOL*, HullPIC, Gubbio, pp.38-49

HOWSE, D. (1980), *Greenwich Time*, Oxford University Press

JIA, H.; PRAKASH, V.; SMITH, T. (2019), *Estimating vessel payloads in bulk shipping using AIS data*, Int. J. Shipping and Transport Logistics

MONTAZERI, N.; PETERSEN, J.B.; HANSEN, S.V. (2019), *Autolog Data Processing for Vessel Performance Application*, HullPIC Conf., Gubbio, pp.211-219

SAFAEI, A.A.; GHASSEMI, H.; GHIASI, M. (2018), *Correcting and Enriching Vessel's Noon Report Data Using Statistical and Data Mining Methods*, European Transport \ Trasporti Europei 67/7 ISSN 1825-3997

SAFAEI, A.A.; GHASSEMI, H.; GHIASI, M. (2019), *Methodology of Acquiring Valid Data by Combining Oil Tankers' Noon Report and Automatic*, Promet - Traffic&Transportation

SCHMODE, D.; HYMPENDAHL, O.; BELLUSCI F. (2019), *Influence of Data Sources on Hull Performance Prediction*, HullPIC Conf., Gubbio, pp.162-171

THEMELIS, N.; SPANDONIDIS, C.; GIORDAMLIS, C. (2018), *A comparative study on ship performance assessment based on noon report and continuous monitoring system datasets*, 2018 Annual Meeting of Marine Technology, 2018/12/04

Speed-Power Models – A Bayesian Approach

Manolis Levantis, Jotun, Sandefjord/Norway, manolis.levantis@jotun.com
Sergiu Paereli, Jotun, Sandefjord/Norway, sergiu.paereli@jotun.no
Alexander Enström, Jotun, Hamburg/Germany, alexander.enstrom@jotun.de
Wolfgang Betz, Eracons, Munich/Germany, betz@eracons.com

Abstract

Hull and propeller performance, especially after the establishment of ISO 19030, has been a major concern for the vessel operators and their energy efficiency departments. However, although latest development in this area is mature, the establishment of vessel models is still an area with a high level of uncertainty. In this paper a gaussian process regression is applied to in-service data to model both speed-power curves and the underlying uncertainty. Furthermore, the mean values of the posterior distribution of the model are used as a speed-power reference curve and the results are compared to widely used speed-power reference curves from speed trials. Finally, the same process is used to model fuel oil consumption and discuss the results.

1. Introduction

Within the last years, energy efficiency in the marine industry was one of the main focus areas. There was big focus on how to design more efficient vessels with significantly improved Energy Efficiency Design Index (EEDI), the overall budget for energy efficiency solutions was drastically increased and several new operational measures were introduced (i.e. slow steaming, performance monitoring, trim optimization, etc.) in order to reduce fuel consumption and CO_2 emissions. In addition, regulators all over the world are focused on several environmental protection measures and marine industry is high on their agenda. Therefore, several regulations/restrictions were imposed which hopefully will result into “greener” vessels.

Although mainly driven by regulators, but not only, the marine industry quickly adopted to these changes and International Maritime Organization (IMO) introduced in 2018 some long-term strategies in an attempt to drastically change the environmental footprint of marine industry. As per *IMO (2018)*, the marine industry should reduce CO_2 emissions per transport work, as an average across international shipping, by at least 40% by 2030 and pursuing efforts towards 70% by 2050, or at least 50% by 2050 and pursuing efforts towards phasing them out compared to 2008. In an attempt to meet these optimistic targets, operators are more and more focused on how to improve operational efficiency of their fleet. One effective way to do that, is to monitor their vessel’s performance and apply corrective actions/ measures when vessel is not performing. So the question is, when does the vessel not perform?

Almost all available methods to answer this question follow the same principles. A model of the vessel is created which in theory describes the vessel’s optimal performance. Through monitoring and data logged from sensors onboard, the deviation from the model is recorded (usually over time). If the deviation is high, the reason for this deviation has to be identified and corrective actions should be taken. It is clear from the above, that having accurate models is critical. Unfortunately, creating vessel models is not an easy task. A vessel’s performance sailing at sea is being affected by many parameters such as vessel design, speed, draft, trim, wind, waves, currents, sea water temperature, hull and propeller condition and many more. Because it is impossible to create a model taking into account all these parameters, engineers are trying to create simplified speed-power models (a model that will predict speed at a given power or vice versa), which account for some of the extra parameters and correct these models accordingly (i.e. ISO 15016).

Recently, two more methods of developing multivariate speed-power models gained popularity. One of them, Computational Fluid Dynamics (CFD), models the water flow and estimates drag coefficients to predict the total resistance to move a specific hull design through water. The alternative to CFD is to use the available data recorded from sensors and use advanced statistical methods (i.e. machine learning) to fit multivariate models to the available data. It is widely accepted that ISO 15016 generates accurate speed-power models. However speed trials are only conducted in very well controlled conditions (usually, but not always), in specific drafts and speed ranges, making it difficult to predict accurately performance outsides the boundaries of these ranges. In addition, it is known that procedures are not always followed correctly on speed trials resulting into speed-power models which are not accurate enough. CFD and machine learning techniques are gaining popularity as previously mentioned, however their credibility remains to be proven.

In this paper we apply a machine learning technique (Gaussian process regression) in an attempt to address three problems. Firstly, to check whether accurate speed-power models can be created when these are either not existing or not accurate. Secondly, to use a Bayesian approach to try to estimate the measured uncertainty and the uncertainty of the model. This is extremely useful as this uncertainty can be propagated at a second stage to relevant Key Performance Indicators (KPIs) and used to make more accurate decisions or prevent from making wrong decisions if the uncertainty is high. Finally, to check whether we can create an accurate enough fuel oil consumption model at a certain measured speed and draft and use this for measuring fuel consumption deviation over time.

2 Proposed probabilistic model

2.1 Overview

We propose a probabilistic model to predict the speed of a vessel based on measurements of power and mean draft. To model the vessel's speed, Gaussian process regression, *Williams et al. (2006)* is used:

$$\mathbf{s}(\mathbf{X}) \sim \mathcal{GP}\left(\mu_{s,\mathbf{X}}, \mathbf{K}_{\mathbf{X},\mathbf{X}}\right) + \boldsymbol{\varepsilon}$$

where:

X represents the measured input data and is composed of the two column vectors **p** and **d**; i.e., $\mathbf{X} = \{\mathbf{p}, \mathbf{d}\}$. Thus, **X** has size $N \times 2$.

N denotes the number of observed data points $\{s_i, p_i, d_i\}, i = 1, \dots, N$.

p is a column vector that contains the N measurements p_i of power delivered to the propeller.

d is a column vector that contains the N measurements d_i of the vessel's mean draft.

s is a column vector of N Gaussian random variables that model the predicted speed of the vessel. More specifically, **s** predicts the measured speed of the vessel – and not the vessel's actual speed.

$\mathcal{GP}\left(\mu_{s,\mathbf{X}}, \mathbf{K}_{\mathbf{X},\mathbf{X}}\right)$ denotes a discretized Gaussian process with mean trend function $\mu_{s,\mathbf{X}}$, and covariance matrix $\mathbf{K}_{\mathbf{X},\mathbf{X}}$.

$\mu_{s,\mathbf{X}}$ is a mean trend function for the vessel's speed that defines the mean of $\mathcal{GP}\left(\mu_{s,\mathbf{X}}, \mathbf{K}_{\mathbf{X},\mathbf{X}}\right)$ before conditioning on **X**.

$\mathbf{K}_{\mathbf{X},\mathbf{X}}$ is the covariance matrix of the Gaussian process.

$\boldsymbol{\varepsilon}$ is a column vector of size N. It is a noise term that accounts for both noise in the measurements and noise in the modelling error. The noise is modeled as a set of N independent Normal random variables with zero mean and standard deviation σ.

2.2 Covariance kernel

The covariance matrix $\mathbf{K}_{\mathbf{X},\mathbf{X}}$ is obtained from the following isotropic covariance kernel with separable length scale:

$$k(p_i, p_j, d_i, d_j) = \eta^2 \cdot \exp\left[-\frac{(p_i - p_j)^2}{2 \cdot l_p^2}\right] \cdot \exp\left[-\frac{(d_i - d_j)^2}{2 \cdot l_d^2}\right]$$

where $i, j \in \{1, \dots, N\}$ and:

η denotes the standard deviation associated with the covariance kernel.

l_p denotes the correlation length that is used to model the correlation between p_i and p_j.
l_d denotes the correlation length that is used to model the correlation between d_i and d_j.

2.3 Mean trend function

The mean trend function expresses the functional shape of how s_i depends on d_i and p_i that one would expect based on physical consideration. In this case, the following functional relation is assumed:

$$\mu_{s_i} = \left(\frac{p_i}{\exp(c) \cdot d_i^w}\right)^{1/v}$$

where the mean trend function $\mu_{s,\mathbf{X}}$ is a column vector of all N values of μ_{s_i}. The quantities v, w and c are parameters whose values need to be determined during calibration of the model. The above functional relation is just one out of many potential function types. The performance with respect to other function types could be assessed in future studies.

2.4 Likelihood function

Given observed input measurements $\mathbf{X}$ and measured speeds $\tilde{\mathbf{s}}$, the likelihood of the observations can be evaluated as the density of a multivariate Normal distribution with mean vector $\mu_{s,\mathbf{X}}$ and covariance matrix $\mathbf{K}_{\mathbf{X},\mathbf{X}}$ evaluated at $\tilde{\mathbf{s}}$.

2.5 Sparse approximation of the Gaussian process

The performance of Gaussian process regression decreases with increasing number of observed data points. The computational complexity of Gaussian process regression is $O(M^3)$ and in terms of memory requirements it is $O(M^2)$, where $M = 2$ for the problem at hand. To use Gaussian process regression in combination with large datasets, sparse approximations can be employed.

In the sparse approximation to Gaussian process regression, K inducing points are selected, where $K \ll M$. The inducing points are "strategically" placed in the input-domain. These points can be – but do not have to be – a subset of the original dataset. The inducing points can be chosen in advance or selected as part of the inference. The computational complexity of a sparse Gaussian approximation is typically $O(K \cdot M^2)$. However, as the full covariance matrix is not assembled, information in the data is compressed and high variance terms in the expansion are neglected. Therefore, the prediction of the Gaussian process is smoothened out.

In the context of this work, we applied the fully independent training conditional (FITC), *Quiñonero-Candela et al. (2005), Snelson et al. (2006),* approach to reduce the computational complexity of the problem at hand. In the FITC approach, the underlying assumption is that the training data is conditionally independent given the inducing points.

2.5 Uncertain model parameters and Bayesian model calibration

The values of following parameters are modelled as uncertain: η, σ, l_d, l_w, c, v, w. For each uncertain model parameter, a weakly informative prior distribution is selected that takes the physically and mathematically feasible parameter space into account. The product of the joint prior density function and the likelihood function is proportional to the posterior distribution. The values of the uncertain model parameters are learned based on recorded measurements $\{s_i, p_i, d_i\}, i = 1, \dots, N$ of a specific vessel. We selected the values for the uncertain model parameters such that the density of the posterior distribution is maximized through application of an optimization algorithm. The uncertain model parameters were fixed to the so-obtained values, which corresponds to the maximum a posteriori probability (MAP) approach.

2.6 Using the model for prediction

Using the above described sparse Gaussian process regression, for each value of power p_* and draft d_*, the mean μ_* and standard deviation σ_* of the predicted speed measurement can be obtained from a conditional multivariate Normal distribution. The covariance between different predicted speeds is not explicitly considered in the context of this work.

3. Application of probabilistic model in theoretical speed

3.1 Mean trend of the probabilistic model versus speed trials (prior distribution)

As previously discussed, the reason for applying the proposed probabilistic model is, firstly, to replicate or correct (if possible) speed-power curves in case they do not exist and, secondly, to estimate the uncertainty of the model and the uncertainty due to noise. In order to validate the model a 14000 TEU container vessel was selected. This vessel is equipped with automatic datalogger acquiring data averaged every 15 minutes and historical data for the last 4 years were made available. Among logged parameters are speed through water, shaft power, fuel consumption, draft aft and fore, wind speed and wind direction, speed over ground and rpm. In order to minimize the effects of possible hull performance deterioration, the first year of data was used as a training set after applied filtering and data cleaning processes. In order to account for calm sea state, true wind values higher than 16 kn were filtered out. The computed coefficients after fitting the model can be seen in Table I.

Table I: Computed coefficients for speed-draft-fuel consumption relationship

c	w	v
-0.78	3.06	0.71

In Fig.1, the measured data are plotted together with the speed-power curves that are predicted from the mean trend of the probabilistic model and compared against the speed-power curves from speed trials. It is obvious that the curve from speed trials in laden conditions is not correct. The two different model curves in ballast conditions appear to be closer in absolute terms and it is difficult to conclude on which one is more correct. When one is interested in monitoring "absolute performance", although not possible as such, *Paereli et al. (2017)*, the position of the curve is very important and in this case, the mean trend of the probabilistic model appears to fit the data better (at least in laden conditions). However, when measuring relative performance, as in ISO19030, the position of the curve is not that important compared to the curve's shape.

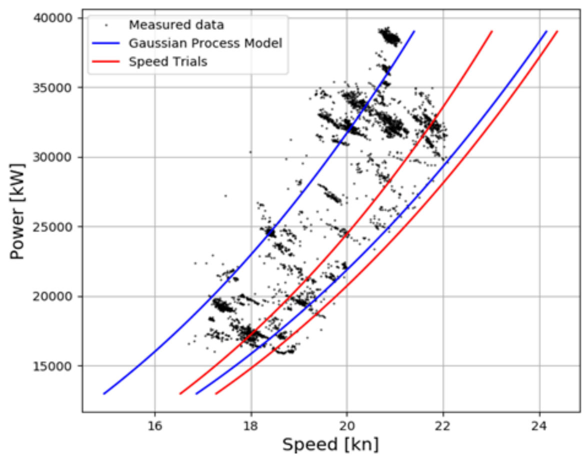


Fig.1: Measured values vs mean trend of probabilistic model and speed trials model

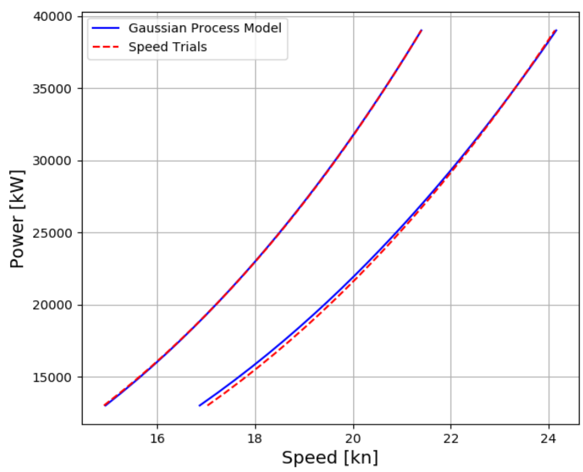


Fig.2: Comparison of curves' shape between the two models

In Fig.2, the speed trial curves are shifted accordingly in order to compare the shape of the curves. The curves in laden conditions between the two models are almost identical. However, comparison of two curves in ballast conditions, shows differences, especially in lower speed ranges. The differences observed in low ranges (~0.2 kn) might be considered significant, however, when speed trials results are not available the mean trend of the probabilistic model can be used as a speed-power curves model in order to quantify changes in hull and propeller performance.

3.2 Maximum a posteriori probability (MAP)

In the previous chapter, the mean trend of the proposed probabilistic model was discussed and evaluated. However, the method applied in this paper does not only predict the mean trend of the theoretical (optimal) speed, but also quantifies the uncertainty in the prediction given the data. Using the sparse Gaussian process regression (described in chapter 2), for each value of power and draft, the mean μ_* and standard deviation σ_* of the predicted speed measurement can be obtained from a conditional multivariate Normal distribution. In order to evaluate the output of the model, the same dataset as in the previous chapter was used.

Fig.3 shows the prediction (posterior belief) of the model for a certain draft (16.1 m). In this speed-power plot, the observed data for a draft range of 0.6 m was plotted (15.8 m - 16.4 m). It is obvious that the prediction is influenced (corrected) based on the existence of data at the draft in question (16.1 m). This is exactly as expected by the Gaussian process regression model. In addition, the two standard deviation intervals are plotted. In ranges better described by data (17.0 kn - 18.0 kn and 19.5 kn - 20.5 kn) the two standard deviation intervals narrow significantly. This means that the uncertainty decreases because there is data in these specific ranges. Finally, in ranges where we don't have enough data the prediction is similar to the mean trend. This is expected as we have no data (evidence) to improve our prior belief.

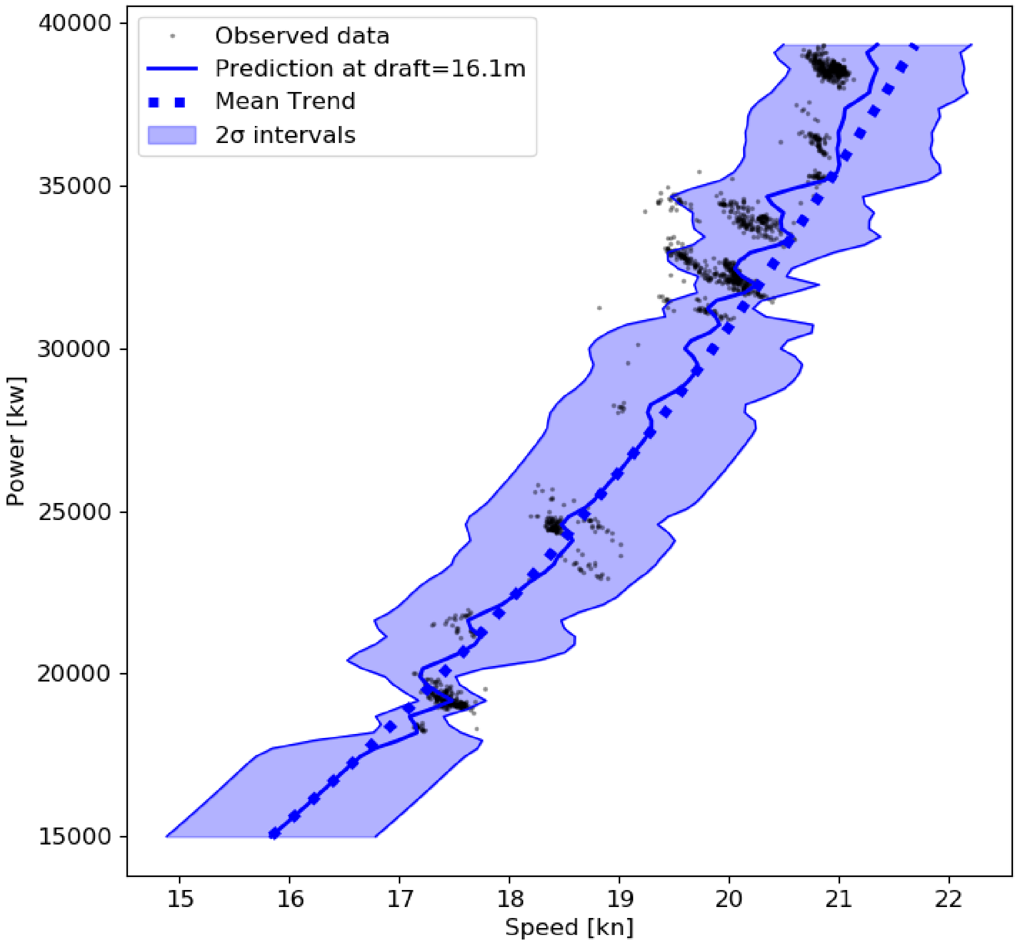


Fig.3: Observed data compared to mean trend and uncertainty bounds of the prediction

In order to evaluate the accuracy of the model and conclude whether this model can be used instead of speed trials model the first year of the available dataset was split into training (75%) and test set (25%). The model was fitted to the training set and the results were compared against the test set. In Fig.4, it can be observed that for most of the test period (with some very small exceptions), predicted speed values are close to the logged values. The standard deviation of the relative error distribution is 2.3%, which in absolute terms means 0.4 kn.

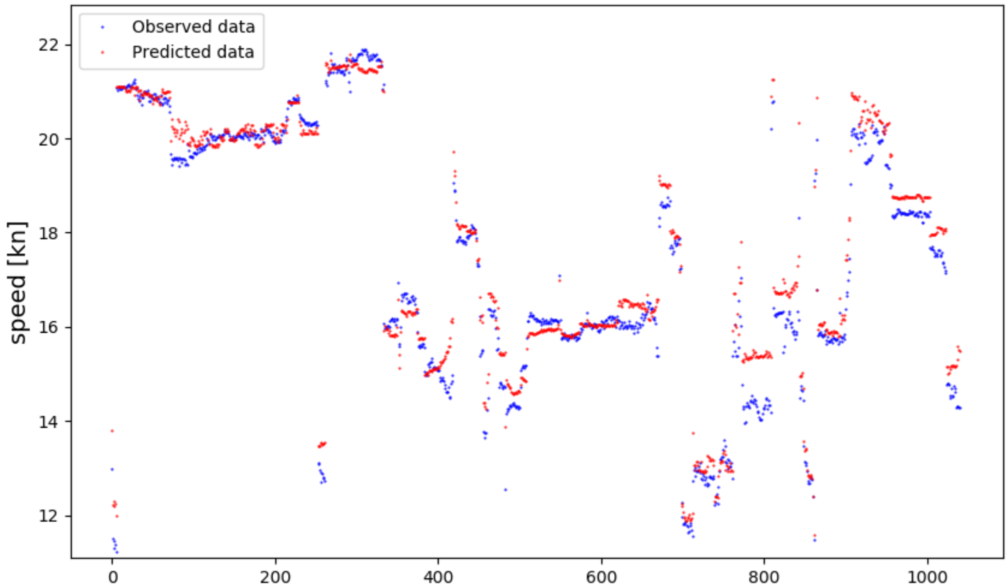


Fig.4: Logged and predicted speed through water (test period)

To conclude whether the proposed probabilistic model can be generally used and not only providing good results in specific cases, same approach as described above has been followed in other three cases (two other containerships and one VLCC). In all cases only the first year of data after dry-docking has been used, 75% of it being the training dataset and 25% - test dataset. In all three cases, predicted speed was found to match very well the logged values.

3.3 Uncertainty

As discussed in the introduction, the purpose of this paper is also to try to estimate the uncertainty of the model and the uncertainty due to noise and apply it in KPIs. In this chapter, the calculation of uncertainty is applied in one of the ISO19030 KPIs (in-service performance) and the results are discussed.

The speed deviation (as per ISO19030) at the ith measurement data-point is:

$$v_{d,i} = \frac{\widetilde{s_i}}{s_i}\text{-}1$$

where $\widetilde{s_i}$ is the speed measured at the respective point, and s_i is the predicted speed for this data point. A first-order approximation for the variance of $v_{d,i}$ is:

$$Var[V_{d,i}] \approx \left(\frac{\widetilde{s_i}}{s_i^2}\right)^2 \cdot Var[s_i^2]$$

Variance of the predicted speed is already provided by the model described here. The same dataset from the same 14000 TEU container was used. A period of 1 month was isolated from the second year of the provided dataset. In Fig.5, the values are plotted together with the error bars at two standard deviations.

For visualization purposes, error bars are plotted every 10 points. The calculated variance from the model can be used in order to calculate the standard error of the mean (SEM). In our example the SEM is 0.05 kn. The 95% confidence interval is given by ±2 x SEM and in our case ± 0.1 kn.

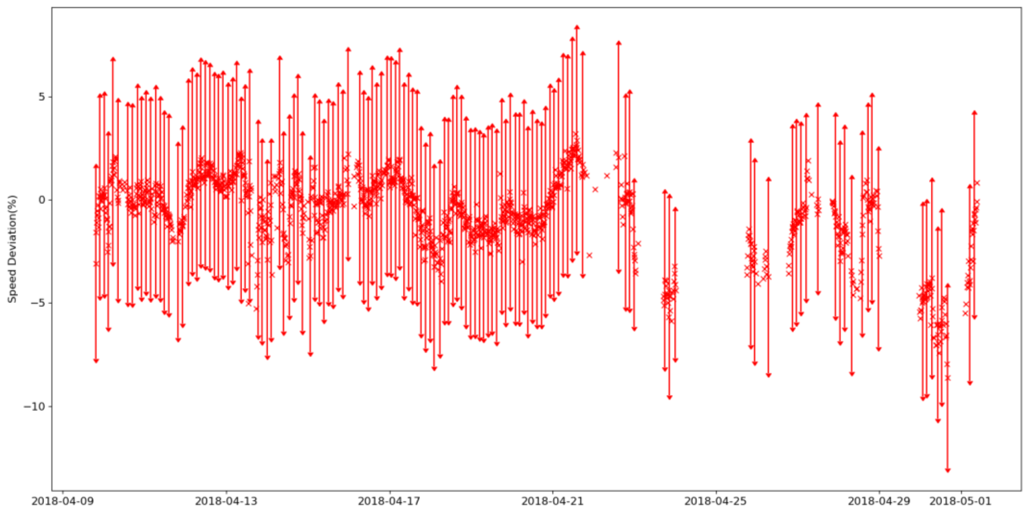


Fig.5: Mean and standard deviation error bars of mean percent speed deviation

4. Further application of probabilistic modeling

As discussed in the previous chapter, probabilistic modeling appears to give good results when predicting vessel's speed through water for given (measured) delivered power and mean draft. Having a trustful model at hand is very useful, especially when speed-power reference curves are not available. This makes it possible calculating speed loss – the performance value mentioned in ISO19030. This standard has gain popularity in the last 3 years and gradually more people can now benefit from using its guidelines towards quantifying the changes in time in their vessels' hull and propeller performance. There are, however, people who are more inclined towards computing a performance indicator based on fuel consumption and there is no wonder why. Being able to compute some sort of fuel consumption deviation, bunker buyers would be very happy to learn directly about their costs increase. Unfortunately, not that many different attempts have been made to somehow quantify changes in vessel fuel consumption in time. ISO19030 supporters usually like the easy, but nevertheless commonly accepted in the industry 1:3 rule of thumb and go down this road. Another big group of people probably try building speed-fuel consumption reference curves by different means. Generally speaking, one can try generating speed-fuel consumption reference curves from logged data by either relying on statistical modeling or probabilistic modeling. Since probabilistic modeling approach by means of Gaussian process regression has been found useful in predicting vessel speed through water, it is decided to further apply it in fuel consumption prediction.

A very similar approach to the one described in the previous chapter has been used for predicting fuel consumption values. A Gaussian process regression model which describes the relationship between vessel speed through water and draft mean is proposed below.

$$FOC = e^{c} \cdot V_S^{v} \cdot D^{w}$$

The proposed model has been built and applied on a dataset from VLCC. This vessel is equipped with automatic datalogger acquiring data every 15 minutes and historical data for the first year since last dry-docking has been made available. Among logged parameters are speed through water, shaft power, fuel consumption, draft aft and fore, wind speed and wind direction, speed over ground and rpm.

Similar to the case when predicting speed through water, the model was built on a training dataset – in this case the first half a year with data (the first half of the reference period in ISO19030 terms). Data has been cleaned for outliers and validated as per ISO19030. Furthermore, data has been filtered for true wind speed below 16 kn, speed above 7.5 kn and fuel consumption values below 120 T/d. The relationship between speed and fuel consumption is shown in Figs.6 and 7.

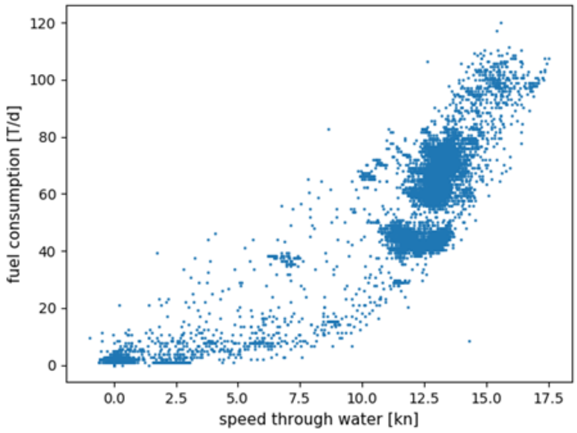


Fig.6: Speed through water - fuel consumption relationship (first half of Year 1)

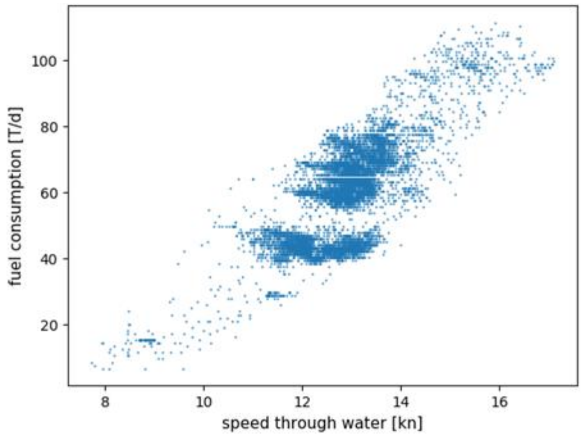


Fig.7: As Fig.6, but cleaned

Upon applying Gaussian process regression on the isolated and cleaned, in a similar way as described above, training dataset, output parameters of the model have been generated, Table II.

Table II: Computed coefficients for speed-draft-fuel consumption relationship

c	v	w
-3.66	2.65	0.31

Once the model is built, ideally, one would compare with other sources such as model tests or speed trials. In this case, however, no other models in terms of speed through water and fuel consumption are available. Therefore, in order to evaluate how good the model is, i.e. what the model uncertainty is, in predicting fuel consumption values, one would need to apply this model on a test dataset. As test dataset the second half of the first year with data has been chosen. The assumption made here is that there is no significant (quantifiable) change in vessel performance in the first year after dry-docking, something that has been documented both visually by inspecting the vessel and by analyzing changes in hull and propeller performance according to ISO19030-2. Since the relationship between speed through water and fuel consumption is not expected to have changed throughout the first year, the model is considered good for use in further vessel performance analysis if predicted fuel consumption values do not differ much from actual logged values. Figs.8 and 9 show results confirming this.

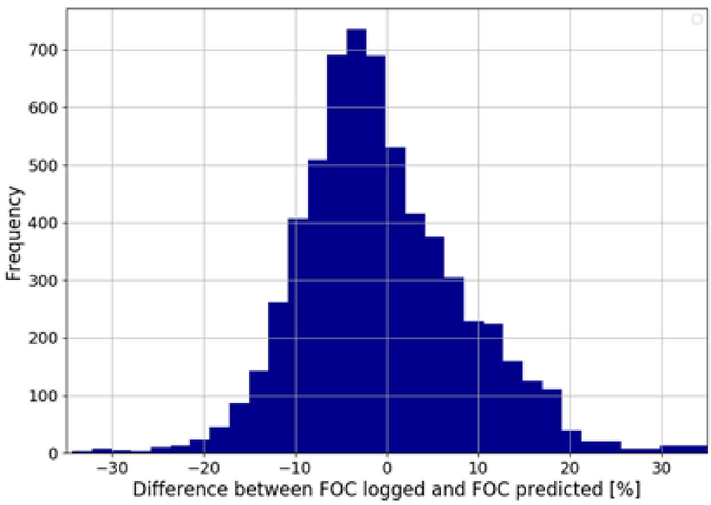


Fig.8: Relative error in FOC prediction

In Fig.9, predicted fuel consumption and logged fuel consumption values are plotted over both training and test periods. In the training period, relative prediction error varies between -2% and 2%. Such a small error is not surprising since this is the data that has been used for training and building the model. It is, however, interesting to see how well the model works on the test dataset. For most of the period (with some very small exceptions), predicted FOC values are close to the logged values. The standard deviation of the relative error distribution in Fig.8 is 10%, which in absolute terms means 5.8 T/d. These relatively small prediction errors, but also slightly larger ones during some short periods, are linked to uncertainties in speed, draft and fuel consumption measurements, but also weather and sea state. To visualize this, the model has been applied to the test dataset which is not filtered for true wind speed. Results are shown in Fig.10.

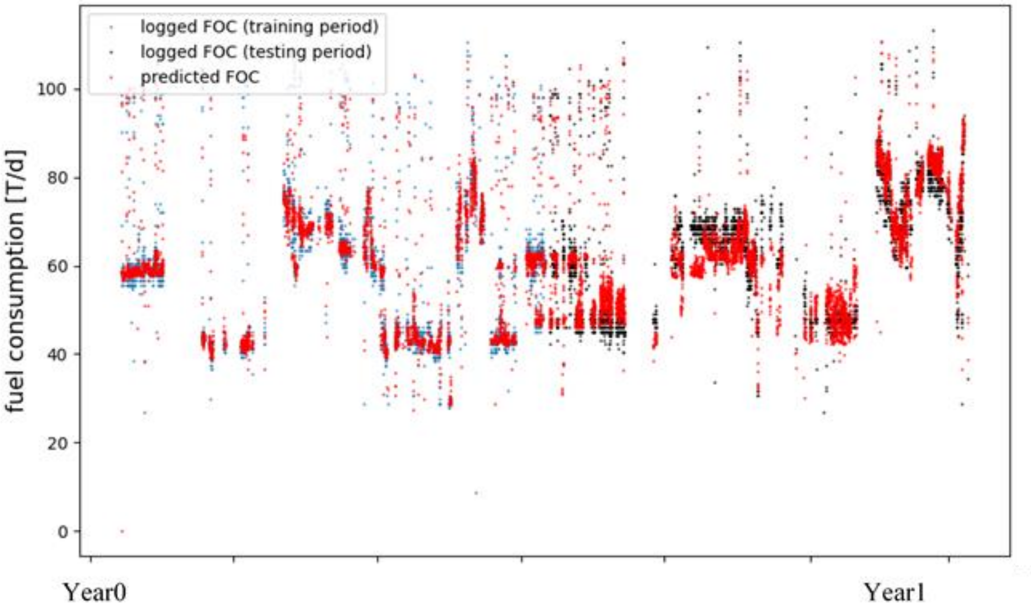


Fig.9: Logged and predicted FOC

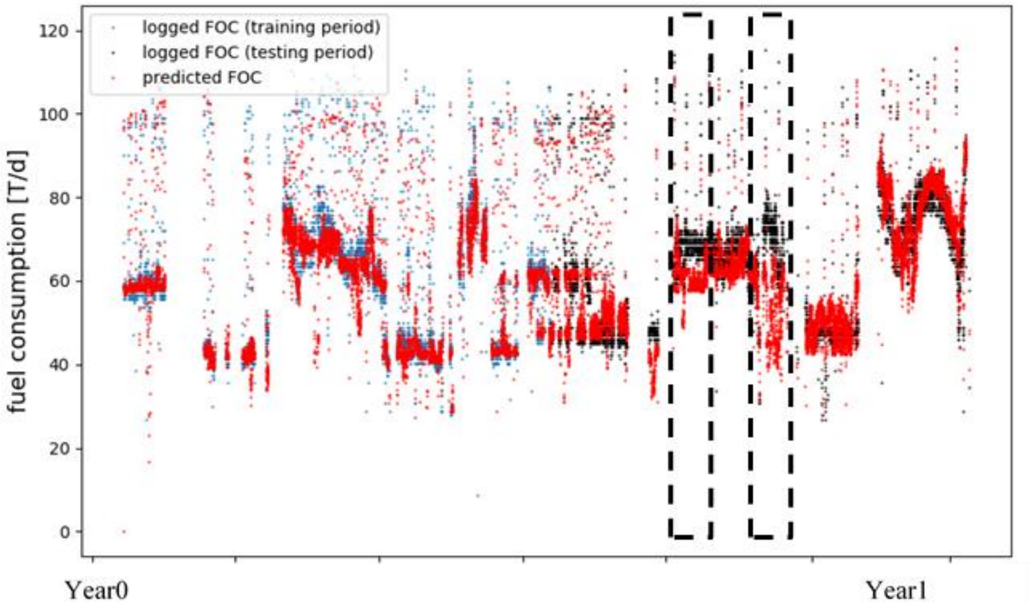


Fig.10: Logged and predicted FOC

The observation to be made in Fig.10 is that during the periods with true wind speed higher than 16 kn in the test dataset (shown with dotted lines), the prediction error increases, just as expected. This is, one the one hand side, because the logged fuel consumption is higher in those periods for the same draft condition and speed through water, and, on the other hand side, because predicted fuel consumption is the “ideal” one – the one computed for conditions determined by the filter used for isolating the training dataset.

The standard deviation of the relative error in periods marked with dotted lines in figure 10 is 16% which in absolute terms means 7.6 T/d. Seeing such differences between logged fuel consumption and predicted (“ideal”) fuel consumption in periods where vessel performance could be concluded stable, for example by running analysis according to ISO19030-2, brings a follow-up idea. One could use this difference to learn about the impact of wind on the relationship between speed through water and fuel consumption. Alternatively, one could try to implement a model in which fuel consumption is a function of not only vessel speed and loading condition, but also function of true wind speed and true wind direction. This is outside of the scope of this paper, but work in this direction will continue.

5. Conclusion

Gaussian process regression was applied to in-service data from several ships. This Bayesian approach helped modeling the vessel specific relationship between speed through water and shaft power. A mean trend function describing the model was proposed, and the latter was fitted to dataset (the first year after dry-docking) from four different vessels. Upon computing the coefficients of the model, this was compared with vessel model (either from model tests or speed trials) provided by vessel owner. In all cases it was concluded that the shape of the computed model is quite similar to the shape of the given model and if the latter had not been made available, computed model could have very well been applied to quantify changes in hull and propeller performance in time.

Furthermore, the applied technique appeared useful in estimating the measured uncertainty and the uncertainty of the model. For evaluating the accuracy of the model, the first year with data after dry-docking was split into a training dataset – to which the model was fit, and a test dataset – on which the model was tested. The chosen split ratio was 75%/25%. Upon applying the built model on the test dataset relatively small difference have been concluded between the predicted values and logged speed through water values. If small prediction error solely represents model uncertainty and not partly also speed through water/draft/shaft power uncertainty, then it could be concluded that in the very end such a model uncertainty results in a standard error of the mean of speed deviation of ±0.05 kn.

Finally, Gaussian process regression has been applied to in-service data from a VLCC for predicting fuel consumption. First, an equation of the model was suggested and then the latter was fitted to a training dataset (the first half a year after vessel dry-docking). After that the built model was verified on a test dataset (the second half of the first year after dry-docking). Predicted fuel consumption values were concluded close to the logged values. Standard deviation of the relative error distribution was 10%, which in absolute terms was 5.8 T/d.

Gaussian process regression was found to be useful in building vessel specific speed-power-draft and speed-fuel consumption-draft models. This approach can, one the one hand side, solve the problem of not having a vessel model available from ship owner, on the other hand side, estimate the uncertainty of the final performance values, and, last but not least, eventually, enable estimation of the effect of other parameters (e.g. true wind speed, true wind direction, etc.) on the performance values.

References

IMO (2018), *Initial IMO strategy on reduction of GHG emissions from ships*, Resolution MEPC.304(72), Int. Maritime Organisation, London
http://www.imo.org/en/knowledgeCentre/IndexofIMOResolutions/Marine-Environment-Protection-Committee-(MEPC)/Documents/MEPC.304(72).pdf

PAERELI, S.; KRAPP, A. (2017), *Hull and Propeller Performance… On an Absolute Scale?*, 2nd Hull-PIC Conf., Ulrichshusen, pp.282-292

QUIÑONERO-CANDELA, J.; RASMUSSEN, C.E. (2005), *A unifying view of sparse approximate Gaussian process regression*, J. Machine Learning Research 6, pp.1939-1959

SNELSON, E.; GHAHRAMANI, Z. (2006), *Sparse Gaussian processes using pseudo-inputs*, Advances in Neural Information Processing Systems, pp.1257-1264

WILLIAMS, C.K.I.; RASMUSSEN, C.E. (2006), *Gaussian processes for machine learning*, MIT Press http://www.gaussianprocess.org/gpml/chapters/RW.pdf

Validation of the Evaluation Method of Ship Performance Using Onboard Monitoring Data - Development of Resistance Criteria Method with Apparent Slip Ratio and Quality Management

Naoto Sogihara, National Maritime Research Institute, Tokyo/Japan, sogihara@m.mpat.go.jp
Akiko Sakurada, National Maritime Research Institute, Tokyo/Japan, sakurada@m.mpat.go.jp
Masaru Tsujimoto, National Maritime Research Institute, Tokyo/Japan, m-tsuji@m.mpat.go.jp
Hidehiko Sato, MTI Co. Ltd.; Tokyo/Japan, hidehiko_sato@monohakobi.com

Abstract

This paper describes the method for evaluating ship performance based on onboard monitoring data developed in the OCTARVIA project which is a collaborative effort of 25 stakeholders in Japan. The authors focus on the resistance increase ratio in actual seas as a key factor for extracting the data which are measured in calm seas. The authors propose RCM (Resistance Criteria Method) for evaluating ship performance using the extracted data and validate the effectiveness of RCM by a comparison between onboard monitoring data and performance simulations.

1. Introduction

Recently onboard monitoring has been widely conducted for evaluating ship performance in service. International Maritime Organization (IMO) has started Data Collection System (DCS) on fuel consumption on January 2019, as a measure for the Greenhouse gas (GHG) reduction strategy. These show that onboard monitoring is becoming a trend and require an accurate method for evaluating the performance based on the onboard monitoring data.

A project for the evaluation of ship performance in actual seas called 'OCTARVIA', in which 25 companies of Japanese maritime cluster collaborate, has been launched on October 2017 and remains a half of year, *Tsujimoto et al. (2020)*. The project organized a working group S1-WG for establishing a method for evaluating the ship performance using onboard monitoring data collected in service, *Sogihara et al. (2019).*

At present, S1-WG discusses establishment of an evaluation method of ship performance in calm seas using onboard monitoring data because the ship performance is the base performance for evaluating ship performance in actual seas or assessing the effect of fouling and aging. On this regard, *ISO 19030* stipulates the procedure for measuring changes in hull and propeller performance, such as data validation, data filtering, and data collection. On the other hand, ISO 19030 does not aim to compare the performance between different ships including sister ships. Furthermore, ISO 19030 does not treat correction for waves.

ISO 19030 describes a specific value for data filtering irrespective of ship size. Specifically, data filtering for evaluation of the ship performance requires criteria of wind speed. However, the effect of winds and waves on the ship performance depends on ship size, which requires more reasonable criteria for data filtering.

S1-WG has proposed an evaluation method of ship performance using onboard monitoring data called resistance criteria method (RCM), including data validation, data correction, data filtering, and acquisition of performance curve in calm seas. RCM incorporates apparent slip ratio for appropriate data filtering and is capable of acquiring the accurate performance curve with quality management.

S1-WG has also validated the effectiveness of RCM through the comparison on fuel oil consumption between onboard monitoring data and the simulation based on the performance curve obtained by RCM.

2. Conventional method

Many studies on the evaluation of ship performance in calm seas using onboard monitoring data have been conducted. The numerical model has been proposed for expressing the ship performance as a relationship among ship speed, engine revolution, and engine output, *Sakurada et al. (2019)*. The numerical model is expressed as Eqs. (1) and (2) where V_S is the ship speed in kn, N_E is the engine revolution in rpm, and P is the engine output in kW. ISO 19030 stipulates that c_n is equal to zero in Eq. (1).

$$P = a_n \cdot N_E^{b_n} + c_n \tag{1}$$

$$N_E = d_{nv} \cdot V_s \tag{2}$$

For the application of Eqs. (1) and (2), the dataset of ship speed, engine revolution, and engine output collected in calm seas should be prepared, which requires data filtering process. Conventionally the criteria of the data filtering have been provided with a certain 'fixed' value; for example, ISO 19030 describes Beaufort scale 4 as criteria for the data filtering.

Let us show the application of the numerical model to the filtered data by the fixed value shown in Table I. Cond. 1 and Cond. 2 correspond to Beaufort scale 4 and 5, respectively. These conditions are applied to the onboard monitoring data of a tanker introduced in the following chapter, which results in Fig.1. The data validation and the data correction for environmental factors are not included here.

Table I: Criteria for data filtering for evaluating ship performance in calm seas

Condition	True wind speed U_w [m/s]	Significant wave height H [m]
Cond. 1	9.8	2.0
Cond. 2	6.9	1.0

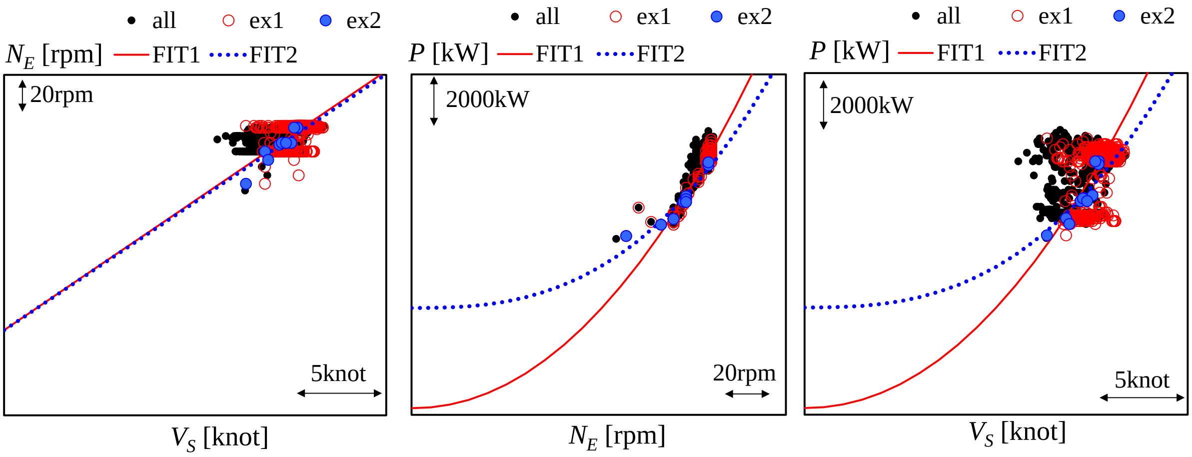


Fig.1: Application of the numerical model to the filtered data by the fixed value

The explanatory notes of Fig.1 are follows:

all	all of measured data
ex1	filtered data by Cond. 1
ex2	filtered data by Cond. 2
FIT1	fitting curve by the numerical model based on the data ex1
FIT2	fitting curve by the numerical model based on the data ex2

Fig.1 indicates that the relationship between ship speed and engine revolution by Cond. 1 and that by Cond. 2 shows good agreement. However, it also indicates that the relationship between engine revolution and engine output by Cond. 1 is obviously different from that by Cond. 2. This result led the authors to consider that it is not appropriate to apply Eqs.(1) and (2) to the data filtered by a 'fixed' value and that universally applicable criteria should be developed.

3. Proposed method

The authors propose an evaluation method of ship performance in calm seas using onboard monitoring data in this paper. The core of the proposed method is resistance criteria method (hereinafter RCM), consisting of the data filtering by apparent slip ratio and the evaluation by the increase rate of added resistance with the quality management. The comparison on flowchart of conventional and proposed method is shown in Fig.2.

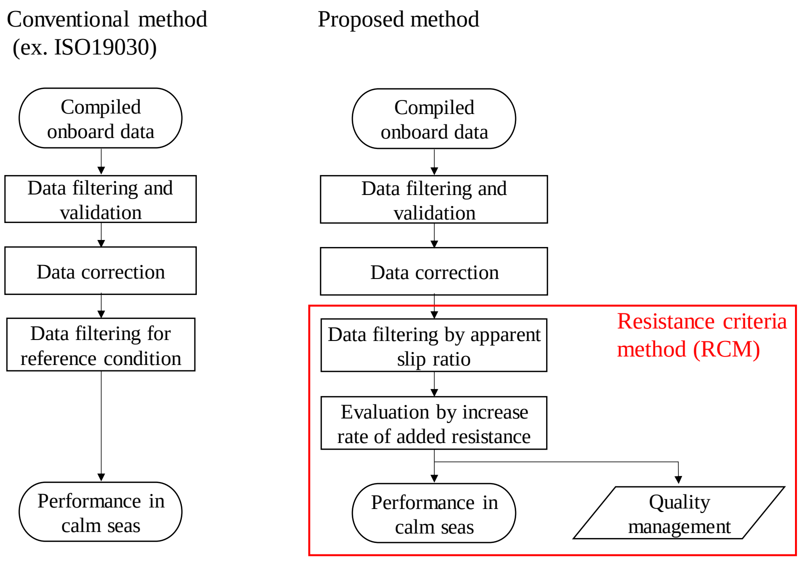


Fig.2: Flowchart of conventional and proposed method

This study introduces two object ships for developing the evaluation method. The principal particulars of the object ships are shown in Table II.

Table II: Principal particulars of the object ships in the study

Ship type	Container ship	Tanker
Length between perpendiculars (L_{pp})	270.0m	185.0m
Breadth (B)	35.0m	32.2m
Design draft (d)	12.0m	13.0m

3.1 Data validation

The data used in the evaluation of ship performance should be deemed as steady condition. For this validation, it is preferable to compute the mean and the standard deviation of the measured parameter for a certain period. ISO 19030 describes that the mean and the standard error of the mean of engine revolution, speed through water and over ground, and rudder angle should be computed for the validation.

While the standard error of the mean or the standard deviation can contribute to the validation, some onboard monitoring systems compute only the mean and not compute such statistical value. S1-WG discussed the criteria for the data validation based on the mean of the measured parameter, which is shown in Table III. 'N_{EMCR}' means revolution at Maximum Continuous Rate of the engine.

Table III: Criteria for data validation

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

* denotes an absolute value.

3.2 Data correction

3.2.1 Correction for displacement

The displacement of a ship in service varies due to the change in the amount of cargo. The combination of the onboard monitoring data measured in some voyages requires the correction for displacement. Firstly, representative displacement is determined based on the operation profile. Secondly, the data which are measured under the displacement close to the representative displacement is selected. In this study, the displacement within 3% of the representative displacement is permitted. Finally, correction for displacement is conducted by the Admiralty coefficient expressed in Eq.(3).

$$V_{rep} = V_{voy}\left(\frac{\Delta_{voy}}{\Delta_{rep}}\right)^{\frac{2}{9}} \tag{3}$$

V and Δ is ship speed through water and displacement, respectively. Subscripts '*voy*' and '*rep*' denote the value in voyage and representative displacement, respectively. Two representative displacements for each ship are determined as shown in Table IV where Δ_{des} means displacement in the design full condition.

Table IV: Representative displacement of the object ships

Ship type	ID	Displacement
Container ship	Group1	$93\%\Delta_{des}$
	Group2	$102\%\Delta_{des}$
Tanker	Group1	$80\%\Delta_{des}$
	Group2	$51\%\Delta_{des}$

3.2.2 Correction for environmental factors

This study treats correction both for winds and waves. The correction is conducted in compliance with Resistance-Thrust Identify Method, *ITTC (2014)*. Added resistance in winds is estimated by the empirical formula, *Fujiwara et al. (2006),* and added resistance in waves is estimated by the theoretical method with simplified tank tests in short waves or empirical formula *Tsujimoto et al. (2008),* which can be expanded to any wave direction, *Tsujimoto et al. (2013)*. This study applies wind data measured onboard and wave hindcast data provided by Japan Weather Association, *Sato and Matsuura (2019),* for the estimation of the added resistance.

Estimation on added resistance in winds and that in waves requires superstructure parameters and hull form parameters such as ship sectional data and waterplane, respectively. Authors prepared such parameters by the simplified method, *Sogihara et al. (2019),* in which these parameters can be estimated by ship type and ship principal parameter.

In addition to above, the correction based on Resistance-Thrust Identify Method requires self-propulsion factors and propeller open characteristics, which are estimated by the simplified method as well as superstructure parameters and hull form parameters.

The results of correction for displacement and environmental factors for Group1 of the container ship and the tanker are shown in Fig.3 and Fig.4, respectively.

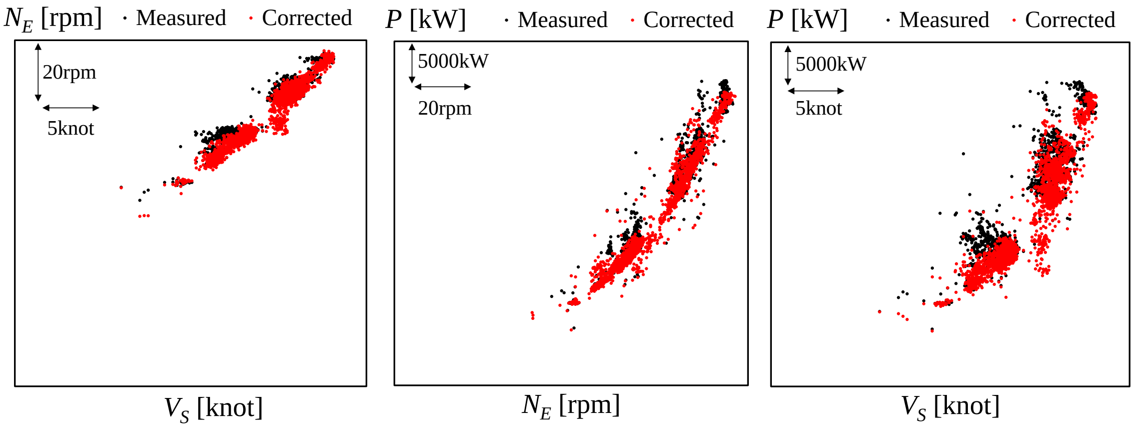


Fig.3: Correction for displacement and environmental factors (Group1 of container ship)

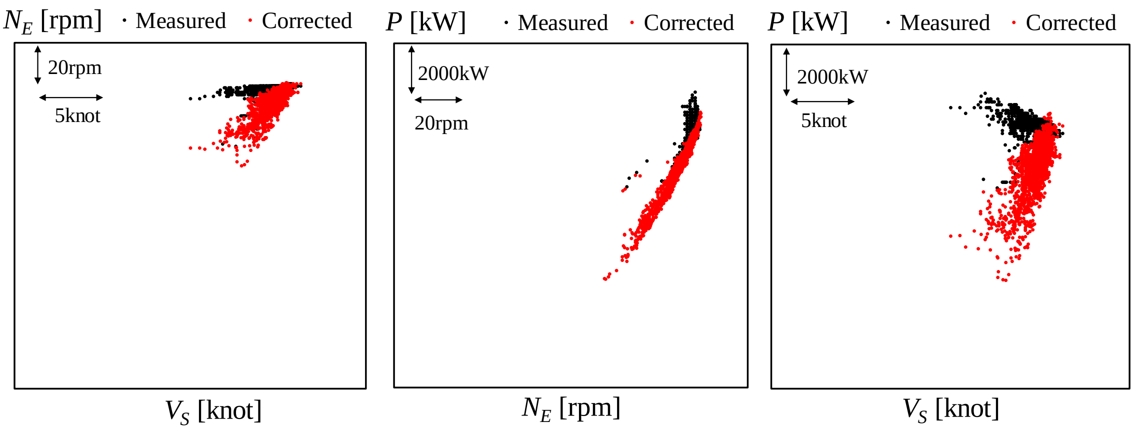


Fig.4: Correction for displacement and environmental factors (Group1 of tanker)

3.3 Resistance criteria method (RCM)

3.3.1 Data filtering by apparent slip ratio

The data which can pass through the data validation and the data correction explained above are often scattered widely because a ship navigates near land at which the accuracy of wave hindcast is reduced. The acquisition of the accurate performance curve requires the data not having scattered, which can be achieved by apparent slip ratio (hereinafter ASR.) S_A. ASR is defined as Eq. (4) where P_p is the propeller pitch and n_{id} is the corrected engine revolution and simplified ASR S_{A0} is calculated by Eq. (5).

$$S_A = 1 - \frac{V_S}{P_p n_{id}} \tag{4}$$

$$S_{A0} = 1 - S_A \tag{5}$$

The mean of simplified ASR of all the data μ_s is obtained by Eq. (6). This study introduces a nominalized simplified ASR nS_{A0} defined by Eq. (7).

$$\mu_s = \frac{1}{N}\sum S_{A0} \tag{6}$$

$$nS_{A0} = \frac{S_{A0} - \mu_s}{\mu_s} \tag{7}$$

The standard deviation of the nominalized simplified ASR σ_s is calculated by Eq. (8). The data which satisfy Eq. (9) is extracted.

$$\sigma_s^{\ 2} = \frac{1}{N}\sum (S_{A0} - \mu_s)^2 \tag{8}$$

$$|nS_{A0}| \le C \cdot \sigma_s \tag{9}$$

This study applies $C = 1.0$ to Eq. (9). The application of the data filtering by apparent slip ratio to Group1 of container ship is shown in Fig 5. Fig.5 indicates that the introduction of apparent slip ratio can reduce the extent of data scattering.

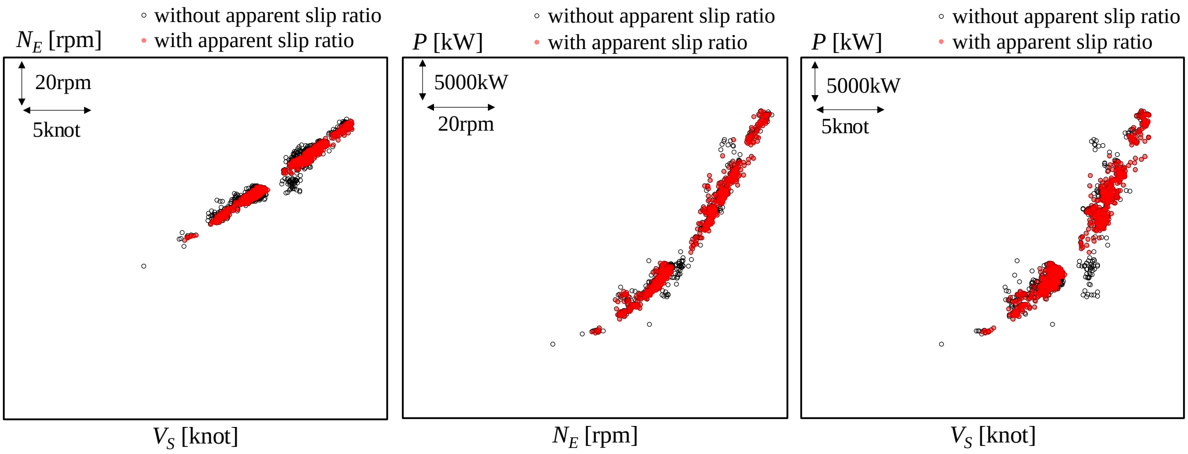


Fig.5: Data filtering by apparent slip ratio (Group1 of container ship)

3.3.2 Evaluation by increase rate of added resistance

After the process of data validation, data correction and data filtering explained above, the data which can provided for the acquisition of the ship performance are obtained. Authors introduces the increase rate of added resistance in order to evaluate the ship performance with high accuracy accompanied with the quality management, *Sakurada et al. (2020)*.

The outline of the evaluation by increase rate of added resistance is illustrated in Fig.6. The key point is that the RCM includes the process of 'two-way' evaluation involving the increase rate of the added resistance δR defined in Eqs. (10) and (11), for enhancing the accuracy of the obtained performance. ΔR is the added resistance in waves and winds, R_{ms} is the resistance in waves and winds, and is R_{ms} is the resistance in calm seas. These parameters are calculated in the process of correction for environmental factors.

$$\delta R = \frac{\Delta R}{R_{id}} \tag{10}$$

$$R_{id} = R_{ms} - \Delta R \tag{11}$$

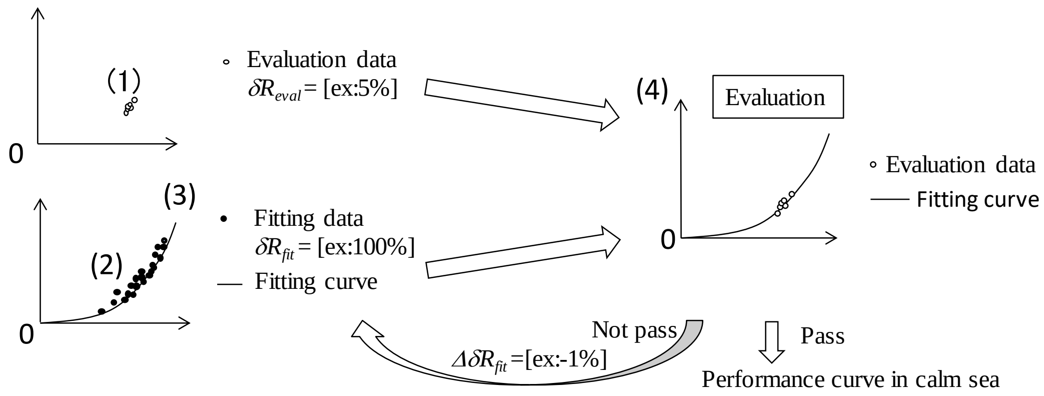


Fig.6: Outline of evaluation by increase rate of added resistance

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.6) 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.6) 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. (1) and (2), which gives tentative performance curve.

After the two ways above, the tentative performance curve is evaluated in conjunction with the evaluation data. RCM introduces the index *EI* defined in Eq. (9) for judging whether the tentative performance curve is acceptable.

$$EI = \sqrt{\frac{\sum_{i=1}^{N} \left\{ d_{norm}(i) \right\}^2}{N}} \tag{12}$$

$d_{norm}(i)$ in Eq. (12) is the distance in normal direction between the evaluation data and the tentative performance curve as shown in Fig.7 where V_{dfc}, N_{Emcr}, and P_{mcr}, denote design ship speed, engine revolution at maximum continuous rate (MCR), and engine output at MCR, respectively. The obtained *EI* is less than the criteria identified specifically, which results in the acquisition of 'final' performance curve.

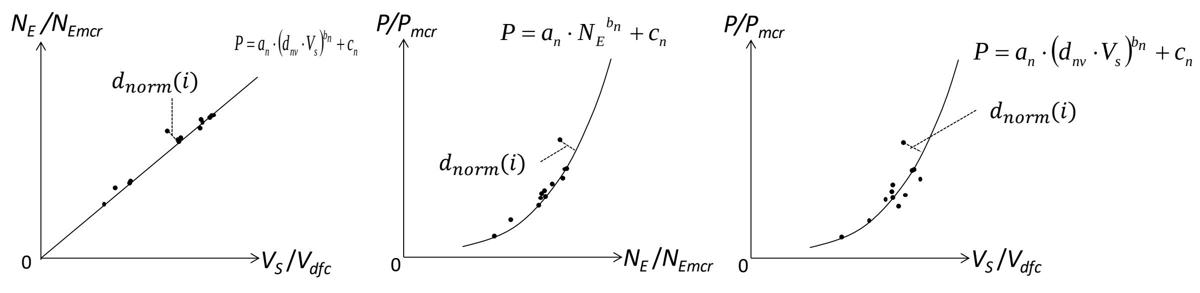


Fig.7: Define of $d_{norm}(i)$

Otherwise, 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 tentative performance curve again and evaluated by the evaluation data. This process is iteratively conducted till *EI* does not exceed the criteria.

3.3.3 Quality management in RCM

RCM has the capability of quality management of the obtained ship performance. The flowchart of the evaluation by increase rate of added resistance is shown in Fig.8. The process described in Section 3.3.2 is the successful case, which is indicated as 'Performance curve (Passed)' in Fig.8.

On the other hand, onboard monitoring data has extreme variation, which can result in fails of the data filtering by δR_{eval} or δR_{fit}. The flowchart of RCM contains branches listed whose functions are defined in Table 5 to obtain the performance curve in such cases. Eventually the performance curve acquired by RCM is provided with the quality management described in Table VI. 'Grade1', 'Grade2', and 'Grade3' is the failed cases of RCM, however, the performance curve is obtained with the quality identification.

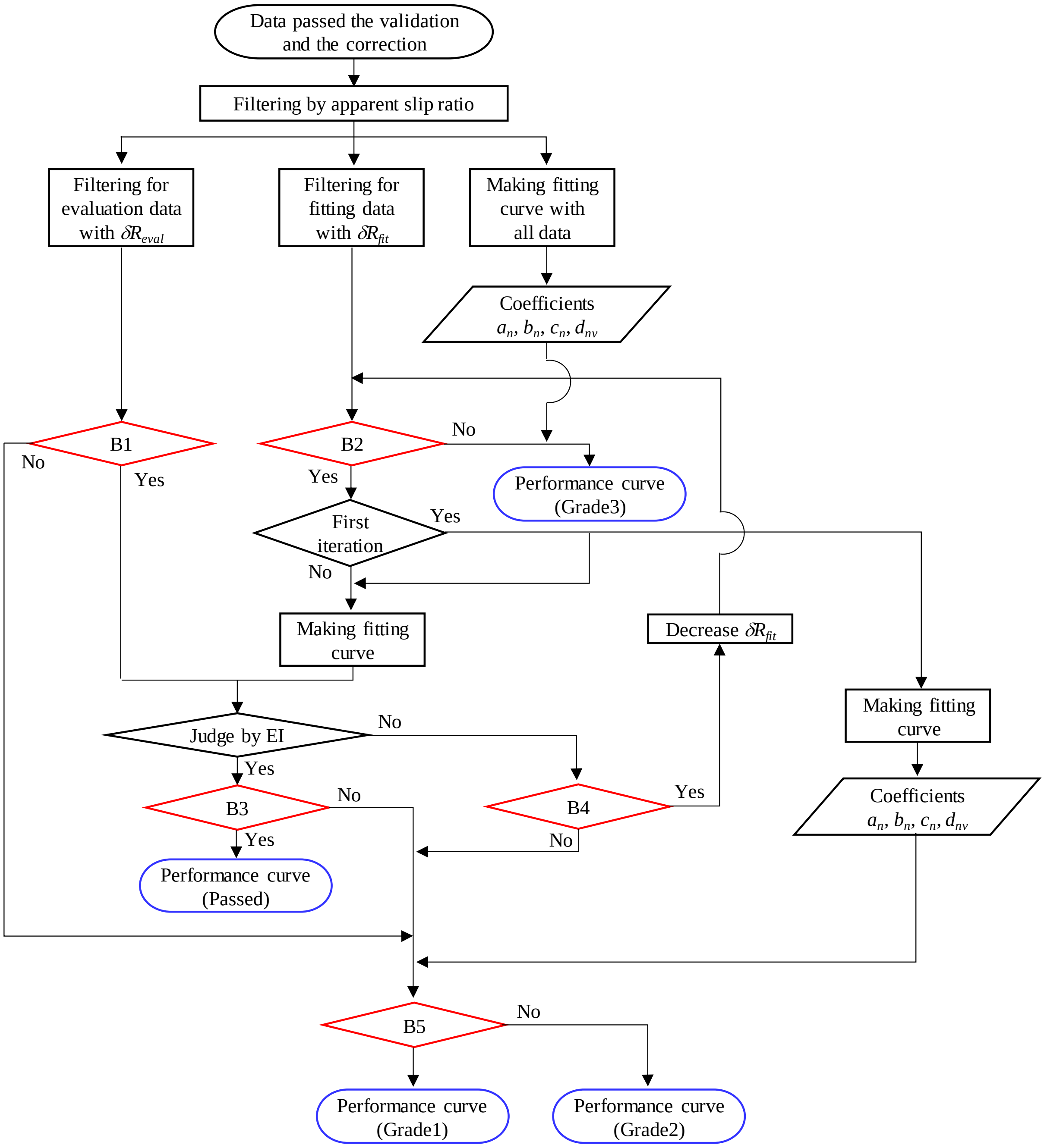


Fig.8: Flowchart of RCM

Table V Functions of the branches in Fig.8

ID	Function
B1	The filtering for evaluation data is successful, which means that the number of the evaluation data is larger than zero.
B2	The filtering for fitting data is successful, which means that the number of the fitting data is larger than zero.
B3	The coefficients of the fitting curve satisfy all the following. a_n and d_{nv} are larger than zero. b_n is between 2.0 and 4.0.
B4	δR_{fit} is larger than 1%.
B5	The coefficients of the initial fitting curve satisfy all the following. a_n and d_{nv} are larger than zero. b_n is between 2.0 and 4.0.

Table VI Qualities identified by RCM

ID	Rank	Quality
Passed	1	RCM is finished completely.
Grade1	2	RCM is not finished completely. The performance curve is obtained by the initial fitting data.
Grade2	3	RCM is not finished completely. The performance curve is obtained by the initial fitting data with b_n = 3.0
Grade3	4	RCM is not finished completely. The performance curve is obtained by all the data with b_n = 3.0

3.3.4 Discussion on numerical model for robust evaluation

The effectiveness of the numerical model expressed in Eqs. (1) and (2) has been validated by onboard monitoring. To enhance the robustness of the evaluation method of ship performance, it is preferable to exclude the intercept of Eq. (1), which yields

$$P = a_n \cdot N_E^{\,b_n} \tag{13}$$

It is necessary to discuss the availability of Eq. (13) in RCM instead of Eq. (1). The authors applied RCM with Eq. (1) and that with Eq. (13) to the onboard monitoring data of the object ships and compared the obtained performance curve between the both. The comparison on the performance curve in calm seas for the object ships is shown in Figs. 9 and 10.

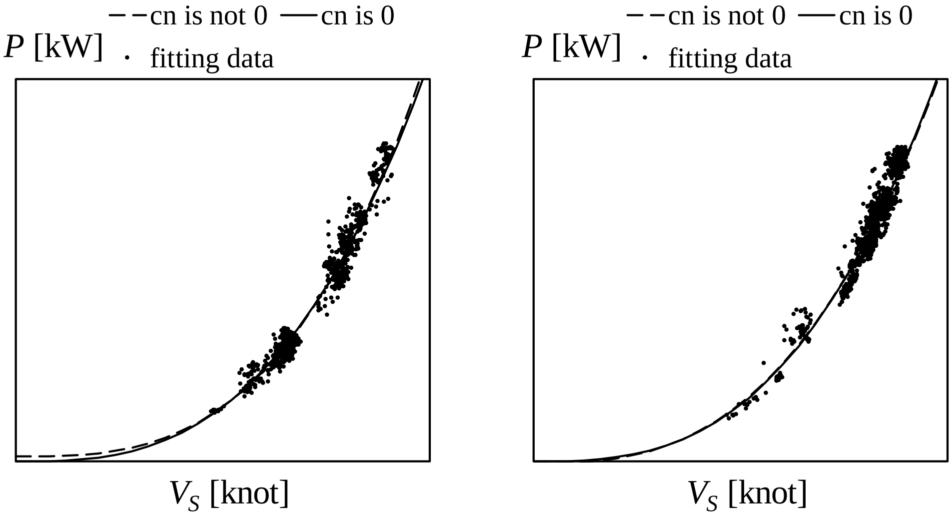


Fig.9: Performance curve of the container ship (left: Group1, right: Group2)

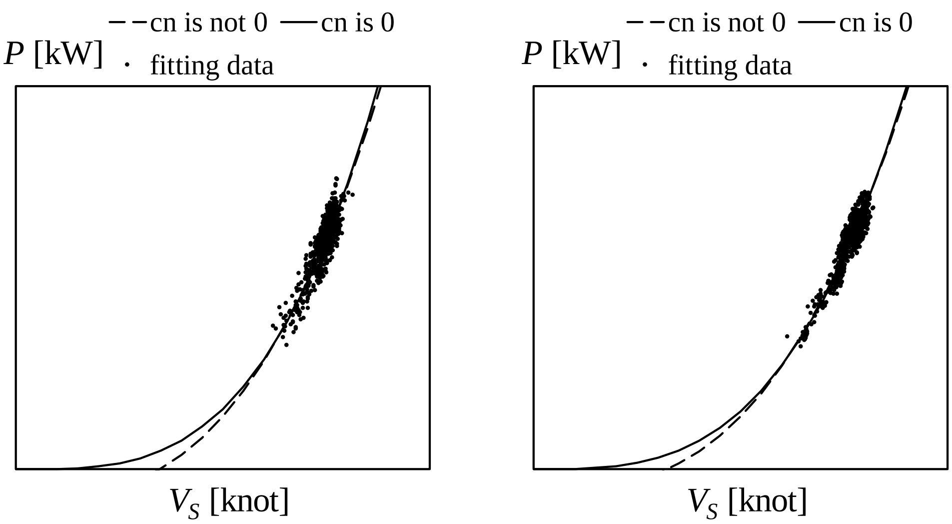


Fig.10: Performance curve of the tanker (left: Group1, right: Group2)

Figs. 9 and 10 shows that the performance curves obtained by RCM with Eq. (1) and that with Eq. (13) almost matches in the speed range at which the fitting data exists. The difference of power at the specific speed in the mentioned range does not exceed 1.5% for both the object ships. Authors confirmed that it is appropriate to incorporate Eq. (13) into RCM for evaluating the performance curve in calm seas.

4. Validation

The proposed method for evaluating the ship performance in calm seas is validated through the comparison on fuel oil consumption between onboard monitoring and the simulation using the ship performance obtained by the proposed method. The simulation is conducted by the ship performance simulator 'VESTA' which can evaluate the ship performance in service such as ship speed, required output, and fuel oil consumption. The effectiveness of VESTA has been validated by onboard monitoring, *Tsujimoto et al. (2015*). VESTA applies the methods described in section 3.2.2 for estimating the added resistance in eaves and winds.

The validation intends to show that the proposed method has a superiority to the conventional method. For achieving that, the performance simulation with the ship performance obtained by the conventional method was conducted. In the conventional method, the application of Eqs. (1) and (2) yields the ship performance in calm seas for each voyage, and the data correction, the data filtering by apparent slip ratio, and RCM are not conducted.

Since the proposed method gives the ship performance for the representative displacement, correction to the performance for the displacement in each voyage is carried out in accordance with the Admiralty coefficient. In this validation, the criteria for the evaluation data δR_{eval} is fixed to 5%. The initial criteria for the fitting data δR_{fit} and the evaluation index EI is provided with 100% and 2%, respectively.

9 voyages of the container ship and 6 voyages of the tanker are subject to the validation. The number of voyages means the summed voyages of Group1 and Group2 shown in Table IV.

For the cases listed in Table VII, the ship performance in calm sea based on the onboard monitoring data is evaluated and it is input to VESTA for the performance simulation of each voyage. U_{wlim} is the criteria of true wind speed and given 7.9m/s. Data filtering of Case-2 includes the criteria of significant wave height H_{lim} in meter expressed by Eq. (14) assuming that the wave effect on a ship depends on its size.

Table VII Cases for the validation

	Conventional		Proposed
ID	Case-1	Case-2	Case-3
Data validation	None		Set as Table 3
Data correction for displacement	None		Admiralty coefficient
Data correction for environmental factors	None		Correction for waves and winds
Data filtering	$U_w \le U_{wlim}$	$U_w \le U_{wlim}$, $H \le H_{lim}$	Apparent slip ratio Increase rate of added resistance

$$H_{lim} = 1.35\sqrt{\frac{L_{pp}}{100}} \tag{14}$$

For example, the comparison between the onboard monitoring and the simulation with the proposed method is shown in Fig.11 for a certain voyage of the tanker. Fig 11 shows the time history of sea state and ship performance in the voyage, demonstrating that the simulation has good agreement with the onboard monitoring. Such comparison was carried out for all the selected voyages of the object ships.

The authors compared δFOC and δL_w defined in Eqs. (15) and (16) among the cases shown in Table V. δFOC and δL_w are difference of the total fuel oil consumption FOC and the distance of navigation L_w in one voyage, between the performance simulation and onboard monitoring, respectively. It is appropriate to demonstrate the superiority of the proposed method based on δFOC and δL_w.

$$\delta FOC = \frac{FOC_{sim} - FOC_{onboard}}{FOC_{onboard}} \tag{15}$$

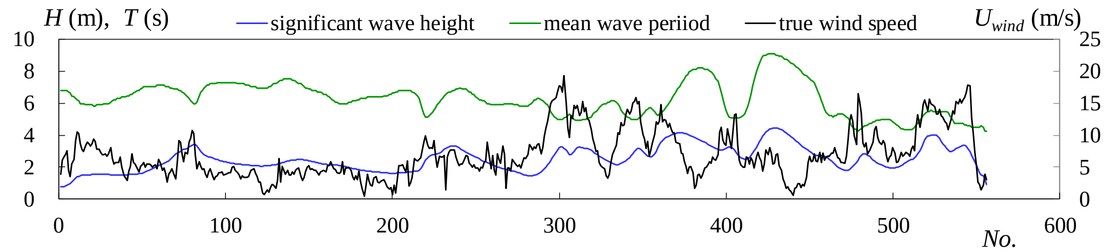
$$\delta L_w = \frac{L_{w_{sim}} - L_{w_{onboard}}}{L_{w_{onboard}}} \tag{16}$$

where the subscripts ‘sim’ and ‘onboard’ in Eqs. (15) and (16) denotes results of the simulation and the onboard monitoring, respectively. Using obtained δFOC and δL_w of all the voyages gives the statistical value such as the mean and the standard deviation, which are shown in Table VIII. The density functions *P.D.F.* of are δFOC and δL_w demonstrated in Fig.12 and Fig.13, assuming that they obey the mean and the standard deviation in Table VIII.

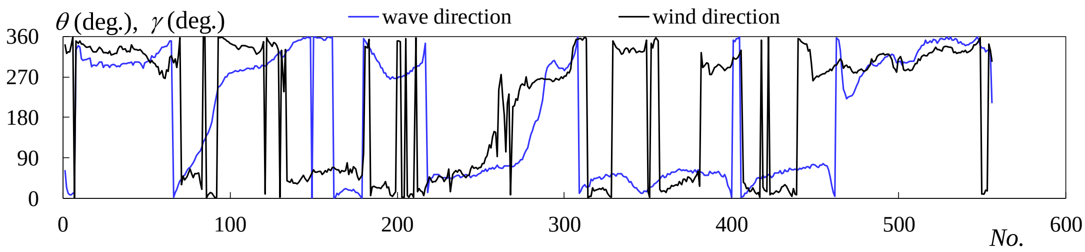
Table VIII: Statistical value on δFOC and δL_w

Item		δFOC (%)			δL_w (%)		
Ship type	value	Case-1	Case-2	Case-3	Case-1	Case-2	Case-3
Container ship	mean	3.8	2.3	3.0	-1.4	-0.8	-0.8
	standard deviation	2.6	2.2	2.8	2.0	0.9	1.2
Tanker	mean	2.4	5.3	0.2	-3.5	-2.5	-0.6
	standard deviation	8.0	0.8	1.0	3.5	2.0	1.0

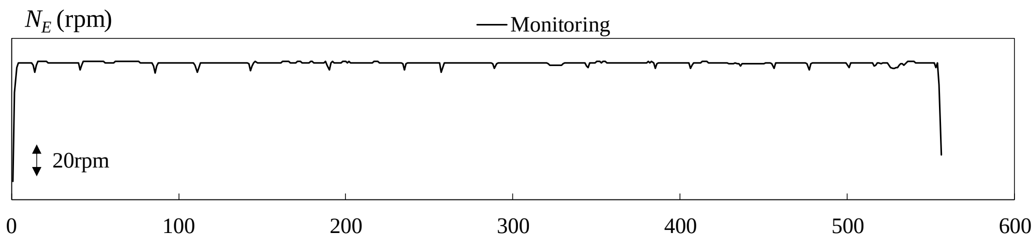
It is expected that Case-3 with correction for environmental factors gives better solution than Case-1and Case-2 without the correction, which is shown in Table III except δFOC of the container ship. For the container ship, the difference in the *P.D.F.* of δFOC and δL_w between Case-2 and Case-3 is small, which means that the data filtering by specific parameters of weather can provide the equivalent performance to RCM for larger ships.



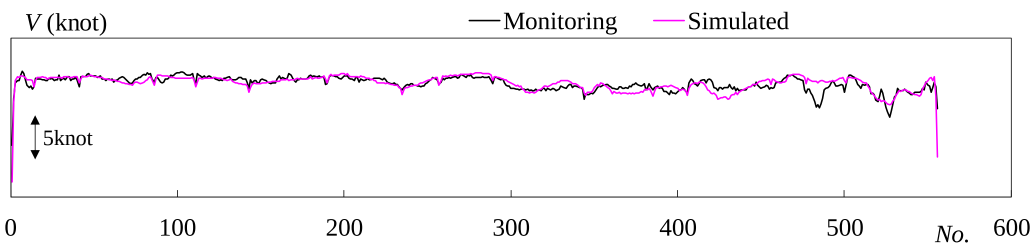
(a) significant wave height (H), mean wave period (T), and true wind speed (U_{wind})



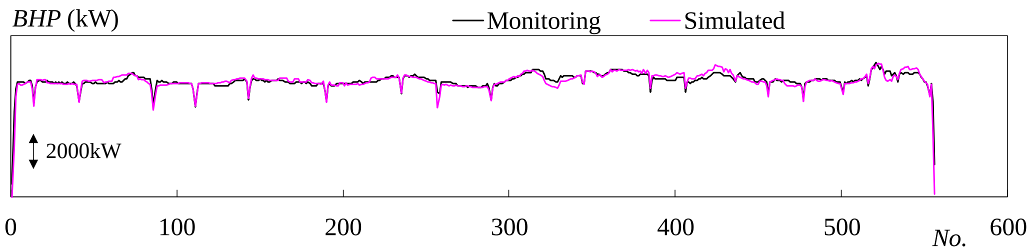
(b) direction of waves (θ) and winds (γ) (0 means heading, clockwise)



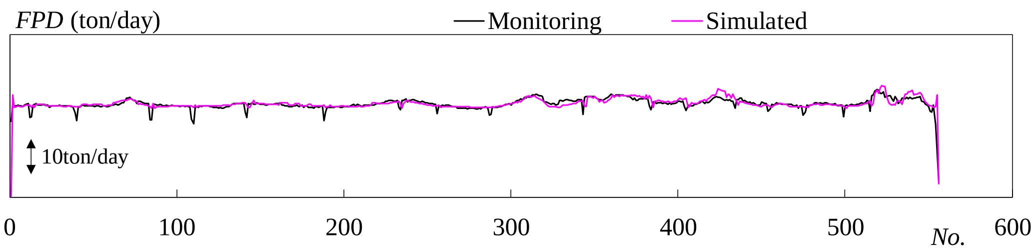
(c) engine revolution (N_E)



(d) ship speed (V)



(e) engine output (BHP)



(f) fuel oil consumption per day (FPD)

Fig.11: Example of comparison between onboard monitoring and simulation for the tanker

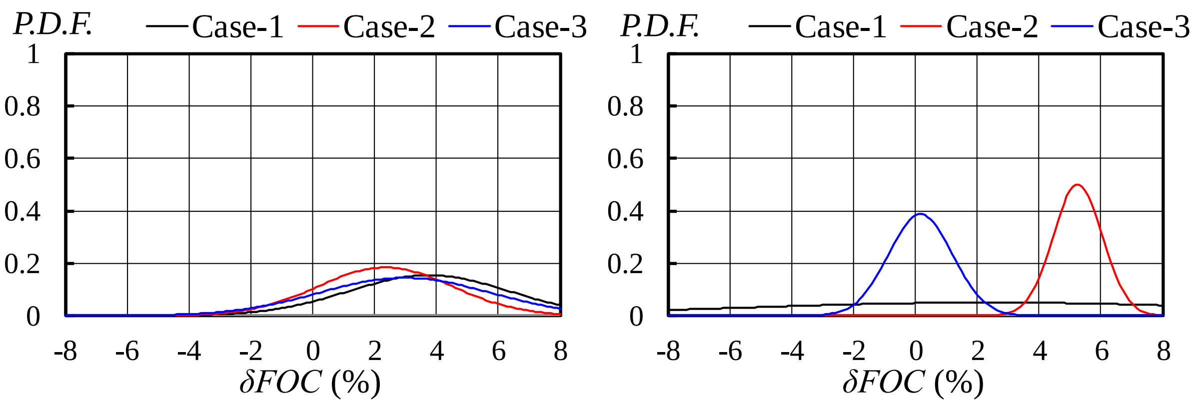


Fig.12 Probability density function of δFOC (left: container ship, right: tanker)

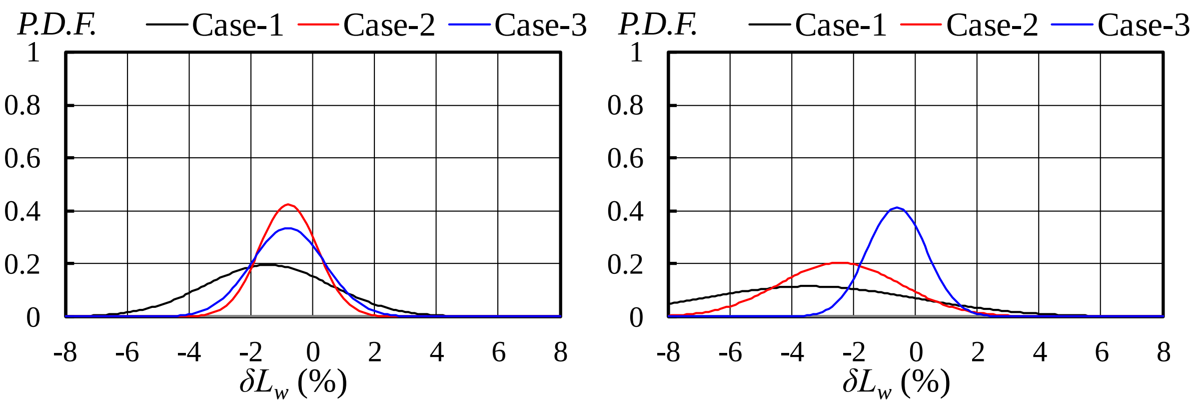


Fig.13: Probability density function of δL_w (left: container ship, right: tanker)

The mean of δFOC of the container ship exceeds 2.0% for all cases since one voyage of the container ship was in slow steaming. The exclusion of the voyage in slow steaming gives lower the mean of δFOC: 3.5% for Case-1, 1.6% for Case-2, and 2.1% for Case-3.

For the tanker, Case-3 provides the mean with the absolute value of δFOC and δL_w less than 1%. It is remarkable that for δFOC and δL_w Case-1and Case-2 are critically different from Case-3. This means that, for the effect of waves and winds is not negligible for the evaluation of the ship performance, and agrees with the fact that smaller ships can be affected by environmental factors.

5. Concluding remarks

This paper proposes resistance criteria method (RCM): an evaluation method of ship performance in calm seas using onboard monitoring data. RCM is comprised of data validation, data correction, data filtering by apparent ratio, and evaluation by increase rate of added resistance due to waves and winds. The features of RCM include the introduction of the apparent slip ratio and the increase rate of added resistance into the data filtering for the reduction of the data scattering which is provided with the quality management function.

For validation of the effectiveness of RCM, the authors conducted the performance simulation with the ship performance in calm seas obtained by the conventional method and RCM. Total fuel oil consumption and distance of navigation in one voyage are calculated by the performance simulator 'VESTA' for 9 voyages of a container ship and 6 voyages of a tanker. The comparison between the simulation and onboard monitoring data clarifies that the RCM has the superiority in evaluating the ship performance in calm seas using onboard monitoring data.

References

FUJIWARA, T.; UENO, M.; IKEDA, Y. (2006), *Cruising performance of a large passenger ship in heavy sea*, ISOPE2006, San Francisco

ISO 19030 (2016), *Ship and marine technology -Measurement of changes in hull and propeller performance*, ISO, Geneva

ISO 15016 (2016), *Ship and marine technology -Guidelines for the assessment of speed and power performance by analysis of speed trial data*, ISO, Geneva

ITTC (2014), *Prediction of Power Increase in Irregular Waves from Model Test* (RP.7.5.-02-07-02.2), International Towing Tank Conference

SAKURADA, A.; SOGIHARA, N.; KURODA, M.; TSUJIMOTO, M.; SUGIMOTO, Y.; HASEGAWA, K.; DANNO, T. (2019), *Application of a Numerical Model on Displacement Correction to the Evaluation of Ship Performance in Calm Seas for a Bulk Carrier Using Ship Monitoring Data*, PRADS

SAKURADA, A.; SOGIHARA, N.; TSUJIMOTO M. (2020), *Development of a Filtering Method for the Evaluation of Performance in Calm Sea Based on Onboard Monitoring Data*, J. Japan Society of Naval Architects and Ocean Engineering

SATO, Y.; MATSUURA, K. (2019), *Forecasting and hindcasting*, The Naval Architect, November, pp.31-34

SOGIHARA, N.; KURODA, M.; SAKURADA, A.; YOKOTA, S.; TSUJIMOTO, M. (2019), *UNITAS: Tool for supporting evaluation of ship performance in actual seas*, Papers of National Maritime Research Institute 19/1, pp. 101-122

SOGIHARA, N.; YONEZAWA, T.; ISHIGURO, T.; SUGIMOTO, Y.; MASUYAMA, S.; MIENO, H.; SHIMADA, M.; MATSUBARA, Y. (2019), *Introduction of OCTARVIA Project: Project for Ship Performance in Actual Seas*, 4th Hull Performance & Insight Conference, Gubbio, pp.21-30

TSUJIMOTO, M.; SHIBATA, K.; KURODA, M.; TAKAGI, K. (2008), *A Practical Correction Method for Added Resistance in Waves*, J. Japan Society of Naval Architects and Ocean Eng. 8

TSUJIMOTO, M.; KURODA, M.; and SOGIHARA, N. (2013), *Development of a calculation method for fuel consumption of ships in actual seas with performance evaluation*, OMAE2013, Nantes.

TSUJIMOTO, M.; SOGIHARA, N.; KURODA, M.; SAKURADA, A. (2015), *Development of a ship performance simulator in actual seas*, OMAE2015, Newfoundland

TSUJIMOTO, M.; SOGIHARA, N.; SATO, H.; KUME, K.; ORIHARA, H.; SUGIMOTO, Y.; KURODA, M. (2020), *Development of Performance Evaluation of Ships in Actual Seas*, 5th Hull Performance & Insight Conference, Tullamore

Investigating Trim Optimisation in Waves for an AFRAMAX Tanker Using CFD

Inno Gatin, In silico d.o.o, Zagreb/Croatia, inno.gatin@cloudtowingtank.com
Michael Servos, Minerva Marine Inc, Athens/Greece, m.servos@minervamarine.com
Hrvoje Jasak, Wikki Ltd, London/UK, h.jasak@wikki.co.uk

Abstract

In the world of ever more increasing constraints on fuel consumption, trim optimisation becomes a more attractive option, which is further emphasized by the decreasing cost of CFD analysis. There is no doubt that trim optimisation can be very useful for fast displacement hulls such as container vessels, but can it be useful for full hull forms such as tankers and bulk carriers? Additionally, is the optimal trim in calm water also optimal in waves? We have conducted a trim optimisation study for an AFRAMAX tanker to find out the answers to these questions.

1. Introduction

Trim and draft optimisation are well-known terms in shipping, and have been used for decades. They are used on various types of vessels, ranging from faster ships such as Ro-Ro and container vessels to slower, fuller hulls such as bulk carriers or tankers. The savings that can be achieved have been proven over and over again, showing significant efficiency increase for most vessels. For full hull form ships the absolute savings are smaller both due to the smaller total power and smaller portion of the pressure resistance in total resistance. Still, it is economically viable to conduct trim optimisation studies for most of these vessels, especially with today's rise of high-fidelity computational methods, and new stricter emission regulations.

While the benefits of trim and draft optimisation in calm sea conditions are well known and fairly well documented, there is little data on the benefits in realistic sea conditions. Ships sailing on long routes can achieve the highest benefit from trim optimisation, but are also often operating in moderate sea conditions. There is very little or no data on whether the trends from calm seas also apply to irregular waves. *Kishev et al. (2014)* reported that an experimental study was conducted to investigate trim optimisation in waves, but very little results are reported in the paper, making it difficult to draw conclusions. Ships crossing the north Atlantic for example spend around 65% of their service in wave conditions corresponding to a significant wave height ranging from 2.5 to 5.5 m, *Hogben et al. (1967)*. These sea conditions significantly increase the power requirements for most ships, and might in general change the trim-draft-speed-power trends obtained at calm sea.

The aim of this paper is to investigate the applicability of trim optimisation data generated using Computational Fluid Dynamics (CFD) for calm sea for the most common sea condition in the north Atlantic. The ship considered is an Aframax vessel spending most of its service crossing the Atlantic. Only head seas conditions are investigated since these have the largest impact on resistance, and since the ship mostly sails in head and following winds when crossing the Atlantic. Calm sea trim optimisation results are also reported in detail, as well as their economic aspect regarding ship operational costs and savings. The software Naval Hydro Pack is used for all simulations.

2. Numerical method

The Naval Hydro Pack is a CFD software based on collocated Finite Volume method which uses Level Set for interface capturing. Special discretisation techniques are employed based on the Ghost Fluid Method to guarantee high accuracy of the two-phase flow model, *Vukčević and Jasak (2017)*.

For trim optimisation, a self-propelled vessel is simulated with two degrees of freedom: heave and pitch. The ship's propeller is modelled using the actuator disc model where a pressure jump is prescribed on a circular surface representing the propeller. The key feature of the algorithm is the ability to assess the undisturbed propeller inflow velocity without the need to perform a separate open water calculation, *Jasak et al. (2019)*. The large number of self-propulsion simulations needed for this study is managed using the automated procedure described in *Gatin et al. (2019)*, minimising human effort.

For simulations in waves, irregular seas are generated in CFD using the JONSWAP spectrum. Waves are introduced into the CFD domain and damped out of it using implicit relaxation zones, *Jasak et al. (2015)*.

3. Vessel characteristics and sailing conditions in calm seas

The subject of the study is an Aframax vessel, Table I:, Fig.1. The ship is simulated with the rudder and a propeller with a diameter of 7.2 m.

Table I: Aframax vessel main particulars

L_{PP}, m	233.0
L_{OA}, m	243.5
B, m	42.0
D, m	21.3
$T_{scantling}$, m	14.5

Fig.1: Side view of the vessel

The sailing and loading conditions for the trim optimisation study in calm seas are selected by observing the operational patterns of the vessel over the years of service. The loading conditions (i.e. drafts) and speeds that are often encountered in service are considered, while having in mind that the most important conditions are the ones corresponding to long voyages. At the same time, the range of the longitudinal static trim of the vessel is selected based on operational limits. Hereafter the positive trim denotes that the ship is trimmed aft with respect to even keel, while trim refers to static trim. The lower limit is mostly dictated by propeller submergence, especially in ballast condition, while the upper limit (bow up trim) depends on operational best practices and crew experience. Setting reasonable limits to the trim conditions that need to be tested reduces the number of overall simulations, lowering the cost of the study.

Table II: Matrix of drafts, speeds and trims tested in calm water

Load Condition No.	Draft [m]	Speeds [kt]	Trims [m]
1	7.0	10, 12, 14	2.5
2	7.2	10, 12, 14	2.0
3	7.5	8, 10, 12, 14	1.0, 1.5, 2.0
4	7.8	8, 10, 12, 14	1.0, 1.5
5	13.0	8, 10, 12, 14	-1.0, -0.5, 0, 0.5, 1.0
6	14.0	8, 10, 12, 13, 14	-1.0, -0.5, 0.0
7	15.0	8, 10, 12, 14	-0.5, 0.0
8	15.5	8, 10, 12, 14	0.0

The list of all drafts, speeds and trims conducted in this study is shown in Table II. The table shows the list of speeds and trims tested for individual loading conditions, i.e. drafts. Every combination of the draft, speed and trim is tested for individual loading condition, resulting in 64 simulations altogether. In ballast condition, some loading conditions only permitted one trim to be tested due to the requirements on the submergence of the propeller. Loading condition 1 and 2 were tested additionally, after the study showed that bow down trim generally saves fuel for larger speeds, which is why only the minimal trim is tested. At maximum draft of 15.5 m the ship is only allowed to operate at even keel.

4. Trim optimisation results in calm seas

We will show now some of the results from the trim optimisation study in calm seas. A few representative load conditions are selected for presentation here in ballast and in fully laden conditions.

Fig.2 to Fig.5 show a few images from the conducted simulations. Fig.3 shows the wave fields for two different velocities and load conditions, where the difference in the geometry of the waterline at the stern can be observed due to a difference in submergence of the transom. Fig.3 (right) shows the wave field generated by the rudder, since the rudder is not fully submerged, see Fig.2 (right).

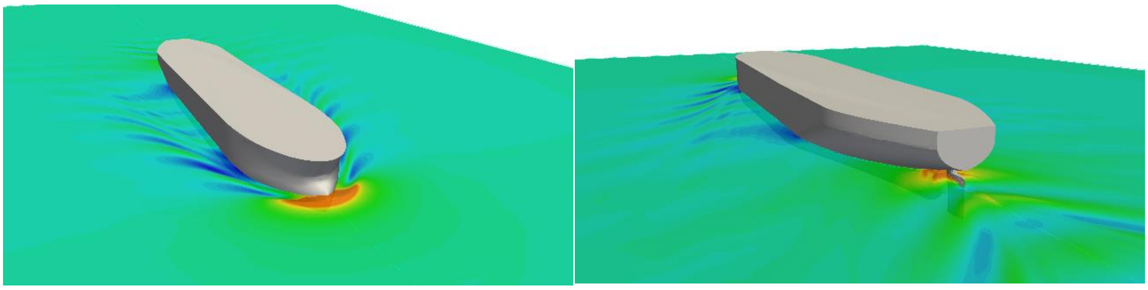


Fig.2: Perspective view of the ship sailing at 14 kn, load condition 3, trim 1.0 m

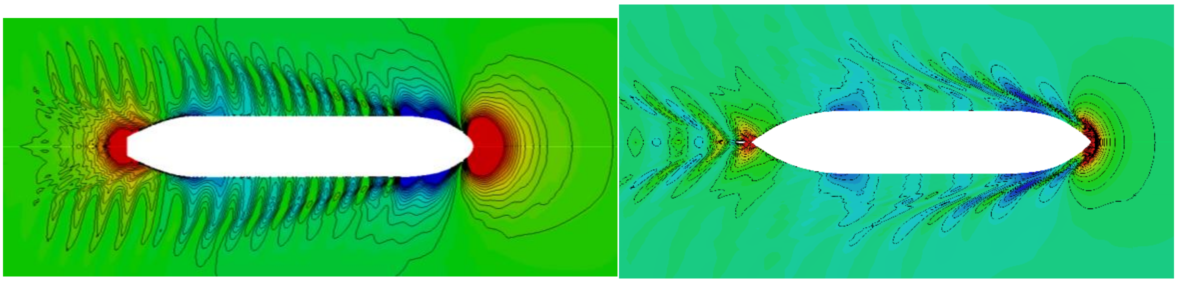


Fig.3: Wave field at 10 kn in load condition 8 (left) and in 14 kn in load condition 3 (right)

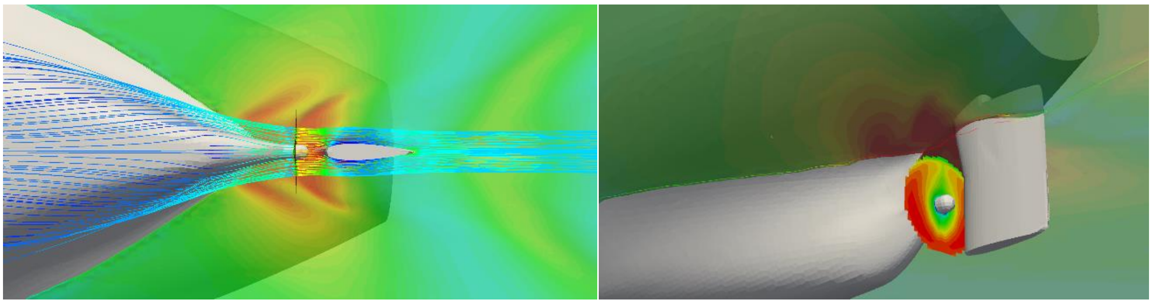


Fig.4: Streamlines showing the flow through the propeller and around the rudder (left), velocity magnitude on the propeller plane (right).

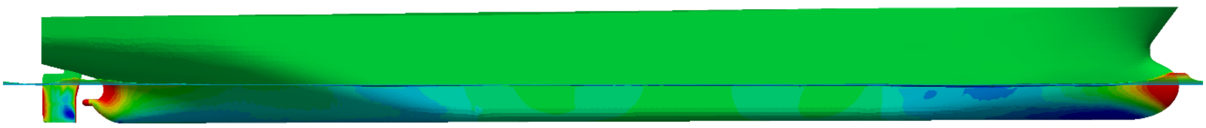


Fig.5: Pressure field along the hull for the ship sailing at 14 kn, load condition 3, trim 1.0 m

Fig.6 shows the power and fuel savings in tons per day for load condition 3 (7.5 m), as an example of the CFD output. For speeds 8-12 kn, the power reduces for bow down trim, while the opposite is true for speed of 14 kn. This shows that the trends are not trivial or easily predicted. At 14 kn, as much as 0.8 tons of fuel per day difference can be observed between trim 2.0 and 1.0 m. Results for load condition 5 are shown in Fig.7, as an example for the laden condition, where the power mostly decreases with decreasing trim, with one exception at 14 kn and -0.5 m trim, where a peak in power is observed. In general, the differences between different trims reach from 0.5 to 1 ton per day of fuel consumption for the largest speed, with similar figures for ballast and laden conditions. At lower speed the differences are significantly smaller: e.g. for 12 kn the maximum differences are typically around 50% of those for 14 kn.

A more relevant representation of these results for the ballast condition is the one where they are compared across different drafts as well as trims, since in ballast it is feasible to change the operating draft. Table III and Table IV: show the power and fuel consumption for the ballast conditions, where the differences are represented across trims and drafts for a given speed. The maximum differences for 8 kn are small, around 0.2 tons/day. At 10 kn, up to half a ton/day can be saved. For 12 and 14 kn, differences up to 0.9 tons/day are observed. Note that the savings that can be achieved depend on the current operational practice, with which the optimum conditions need to be compared. This is reported in section 6.

For the laden conditions, a different representation is needed, since the draft is dictated by the amount of cargo. Here, the only freedom is in changing the static trim. For this vessel (as most tankers), the usual operational practice is to sail at even keel for laden condition, meaning that any savings compared to even keel are relevant. Table V relative differences in fuel consumption for laden loading conditions between even keel and the optimum trim, while Table VI shows the corresponding optimum trims. In general, savings can be expected ranging between 0.1 and 0.3 tons per day.

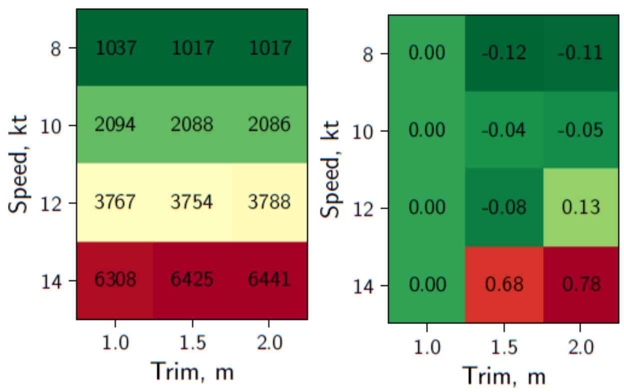


Fig.6: Power in kW (left) and fuel savings in tons per day with respect to trim of 1.0 m (right) for different speeds and trims for Load condition 3

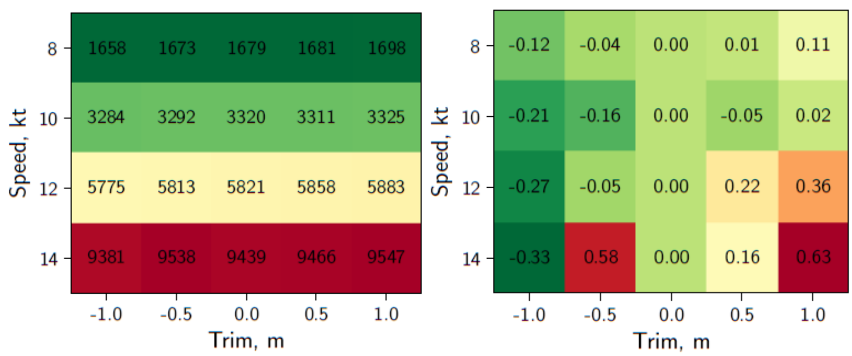


Fig.7: Power in kW (left) and fuel savings in tons per day with respect to even keel (right) for different speeds and trims for Load condition 5.

Table III: Power in kW for different trims and drafts in ballast condition. Colour indicates the relative difference of power for a given speed (green denotes lower power and red higher).

	Draft, m	7	7,2	7,5	7,5	7,5	7,8	7,8
	Trim, m	2,5	2	1	1,5	2	1	1,5
Speed, kt	8			1037	1017	1017	1059	1044
	10	2022	2033	2094	2088	2086	2121	2122
	12	3680	3689	3767	3754	3788	3867	3856
	14	6264	6361	6308	6425	6441	6463	

Table IV: Fuel consumption in tons per day for different trims and drafts in ballast condition. Colour indicates the relative difference of fuel consumption for a given speed (green denotes lower consumption and red higher).

	Draft, m	7	7,2	7,5	7,5	7,5	7,8	7,8
	Trim, m	2,5	2	1	1,5	2	1	1,5
Speed, kt	8			6,1	5,9	5,9	6,1	6,1
	10	11,4	11,4	11,8	11,7	11,7	11,9	11,9
	12	19,6	19,7	20,1	20	20,2	20,5	20,5
	14	31,6	32,1	31,8	32,4	32,4	32,5	

Table V: Fuel consumption savings in tons per day for laden loading conditions. Negative values indicate savings.

Speed/Draft	13	14	15	15.5
8	-0.1	-0.1	-0.2	0
10	-0.2	-0.1	-0.3	0
12	-0.2	-0.2	-0.3	0
14	-0.3	0.0	-0.5	0

Table VI: Optimum trims for individual speed/draft combinations in laden conditions

Speed/Draft	13	14	15	15.5
8	-1	-1	-0.5	0
10	-1	-1	-0.5	0
12	-1	-1	-0.5	0
14	-1	0	-0.5	0

5. Trim optimisation in irregular waves

In order to investigate whether the above study can be applied for realistic sailing conditions encountered by the vessel, a representative sea state is selected, and average power requirements are calculated for some of the sailing conditions. Given the relatively high cost of these simulations, the sailing conditions as well as sea condition are selected in a way to maximise the represented operational conditions. The vessel often sails across the north Atlantic, and according to the ships log the most common sea state corresponds to the Beaufort scale values between 4.5 and 5. For the analysis, a midpoint is selected, i.e 4.75 Beaufort, which corresponds to the following sea energy spectrum values:

- Significant wave height, H_S = 2.04 m,
- Peak period, T_P = 8.3 s,
- Wind speed = 17.6 kt.

According to the Global Wave Statistics, *Hogben (1967)*, this sea state has a probability of occurrence of around 6.5%, and it resides in a region of the table surrounded by high probabilities. This verifies the values from the log up to some extent and gives confidence in the selected sea state to represent a realistic and common condition.

In the CFD simulation, the JONSWAP spectrum is used to determine the individual wave components based on the above spectrum characteristics. The simulated conditions are listed in Table VII, while Fig.**9** shows a ship sailing in ballast condition. In the simulations, the vessel had a prescribed velocity, and the propeller was instructed to achieve a zero average net force on the vessel. This means that the rotation rate of the propeller varied in the simulation, which is not the exact replication of real-life conditions, where constant RPM is maintained. The reasoning behind this approach is that if a constant RPM was selected, different sailing conditions would differ in ship speed. It would then be difficult to compare different conditions in terms of power, i.e. fuel consumption. In order to minimise statistical errors, all simulations are performed with identical phase shifts of individual wave components, to allow a quasi-deterministic comparison. This might result in an error of absolute added resistance in waves; however, the comparison between different loading and trim conditions is very accurate. To optimise the calculation time the duration of simulated full-scale time is reduced to 15 minutes.

In order to ensure result quality in such a short amount of physical full-scale time, a comparison of total power is performed for a signal averaged after 15 minutes, and after 30. Fig.**8** shows a power signal over 1950 s of simulated time for Load condition 3, trim 2.0 m. The black line indicates the entire power signal, the red is the signal from 100 to 1000 s (15 minutes), and the blue represents the signal from 100 to 1900 s (30 minutes). Note that the first 100 s are excluded to prevent any quasi transient effects to influence the results. The average power calculated for 15 minutes is 4377.18 kW, while it is 4387.22 for 30 minutes. The relative difference is therefore 0.2 %, which is acceptable but should be kept in mind when analyzing the results of this study.

Table VII: Matrix of drafts, speeds and trims tested in waves

Load Condition No.	Draft [m]	Speeds [kn]	Trims [m]
1	7.0	12, 14	2.5
2	7.2	12, 14	2.0
3	7.5	12	1.0, 1.5, 2.0

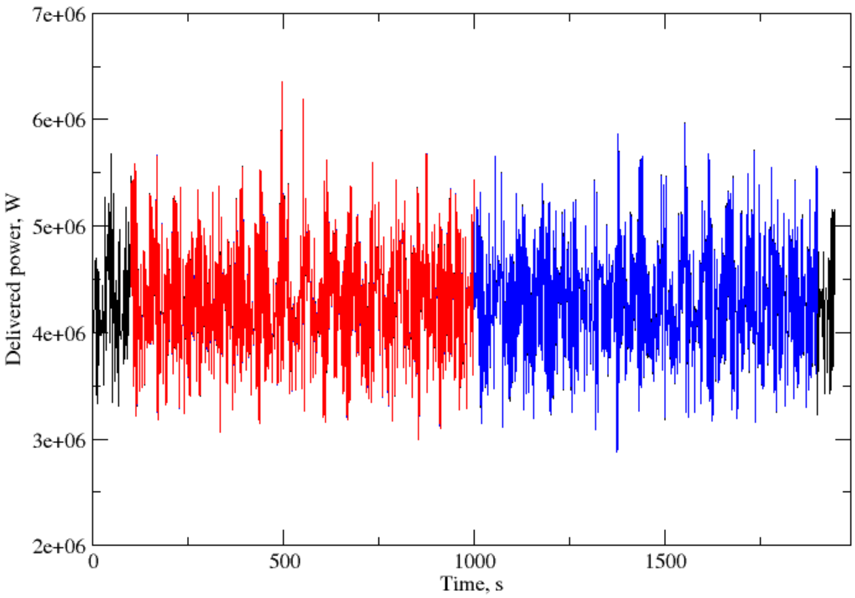


Fig.8: Time signal of the power delivered to the propeller during a simulation in irregular waves for load condition 3, trim 2.0 m. The black line is the entire simulated signal, the red is the signal from 100 to 1000 s, and the blue from 100 to 1900 s.

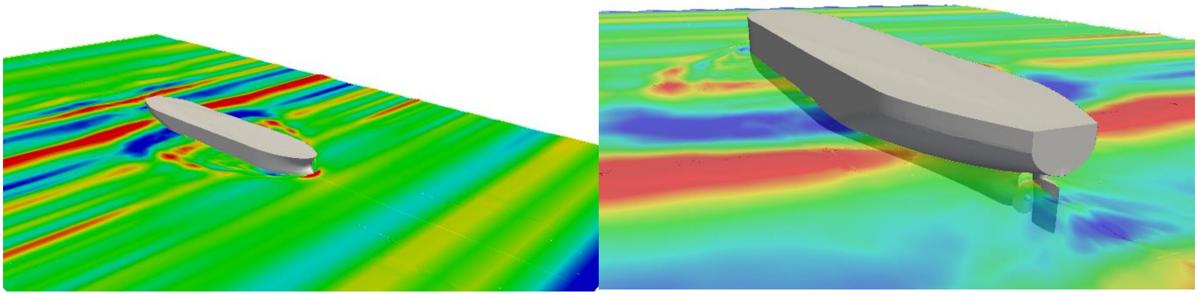


Fig.9: Simulation of a vessel sailing in irregular head waves

Average power delivered to the propeller and fuel consumption for different sailing conditions is summarized in Tables VIII and IX, respectively. Overall, the differences in power between different drafts/trims are larger than in calm water. For speed of 12 kn, the largest difference in power is 5.8 % in waves, and 4.95 % in calm seas, or in absolute values, 187 versus 253 kW. Fuel savings also follow this trend, where up to 1.2 tons per day can be saved in waves at 12 kn versus 0.9 in calm seas.

The main purpose of the study in waves is to determine whether the trends of power dependency on speed, trim and draft are equivalent in waves. Table X: gives a heat map of the calculated power in 12 kn in calm seas and irregular head waves, while Fig.10 shows the same data in a graph. The trend is similar, showing that calm seas results represent the trends in waves very well for this case.

Table VIII: Power in kW delivered to the propeller in irregular head waves

	Draft	7	7,2	7,5	7,5	7,5
	Trim	2,5	2	1	1,5	2
Speed	12	4194	4306	4432	4401	4447
	14	6832	7033			

Table IX: Fuel consumption in tons per day in irregular head waves

	Draft	7	7,2	7,5	7,5	7,5
	Trim	2,5	2	1	1,5	2
Speed	12	22,1	22,6	23,2	23,1	23,3
	14	34,2	35,1			

Table X: Comparison of power in calm seas and irregular head waves for 12 kn

Draft	7	7,2	7,5	7,5	7,5
Trim	2,5	2	1	1,5	2
Condition. No	1	2	3	4	5
Calm seas	3680	3689	3767	3754	3788
Waves	4194	4306	4432	4401	4447

6. Economic aspect – savings in operations, ROI

Based on the actual operational profile of the vessel, and the above results, the actual savings in terms of tons of fuel per year are calculated. For the ballast condition, the current practice is to sail at draft of 7.2 m and 2.0 m trim. The optimum condition is to sail at 7.0 m and 2.5 m trim. The difference between these two conditions, i.e. the fuel savings in tons per day are shown in Table XI. For 10 kn there are no savings in calm sea, and the data in waves are not available. For the analysis that follows, we assumed that there are no savings in waves either. Using this data and applying it to the operational profile of the vessel, the total yearly fuel savings are calculated. Fig.11 shows the distribution of ship speed relative to the total amount of time the ship spends sailing in ballast condition per year.

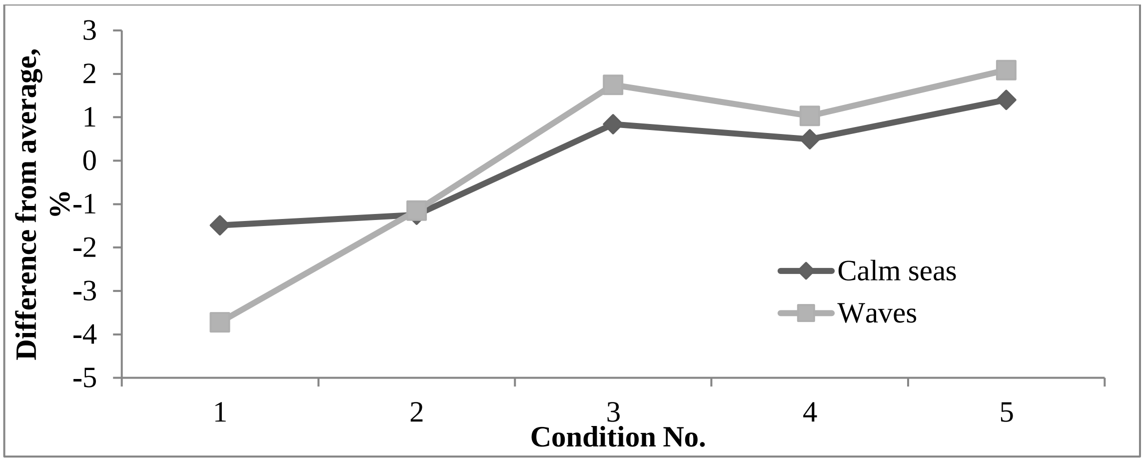


Fig.10. Comparison of power trends in percentages of the average value between calm seas and irregular waves results for speed of 12 kn

Similar can be done for every draft in laden conditions. Table XII summarizes the fuel savings for all loading conditions, where the savings are weighted with the relative frequency of individual loading condition in a year. For ballast, where the trim optimisation data in waves are available, savings in waves are also included. Note that the ship is active 70% of the year. Based on Table XII, the total savings per year range from 44.2 tons to 69.5 tons, depending on the weather conditions during operations in ballast. With the current HFO prices (in Rotterdam), this is equal to approximately 18 500 to 29 000 USD per year.

The vessel in this particular study is one out of seven sister ships, which needs to be taken into account when estimating the Return Of Investment period (ROI). The total cost of the CFD trim optimisation study, without taking into account simulations in waves, is around 22000 USD, including the generation of the 3D model of the vessel. The simulations in waves cost relatively more, but are not a part of a standard trim optimisation study. This gives a ROI period of less than two months for the more conservative savings of 18500 USD per ship. The ROI is likely to be even shorter given that the vessel operates in waves a portion of its service. It should be noted here that effects of trim are not investigated in following waves, or other encounter angles, which needs to be kept in mind.

Table XI: Fuel savings in tons per day for ballast condition

Speed	Calm Sea	Waves
10	0.0	N/A
12	0.1	0.5
14	0.5	0.9

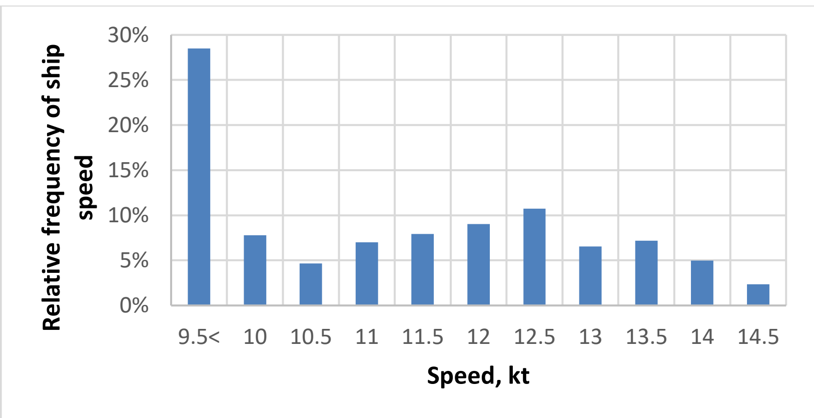


Fig.11: Relative frequency of ship speed in ballast condition

Table XII: Fuel savings achieved per year given the relative frequency of individual loading conditions, for calm sea conditions

Loading condition (draft)	Ballast, calm sea/waves	13 m	14 m	15 m	15.5 m
Fuel savings (t/day)	0.12/0.45	0.22	0.16	0.34	0
Relative frequency of the sailing condition per year	21%	13%	19%	11%	1%
Fuel savings per year, t	9.2/34.5	10.1	11.0	13.9	0.0

7. Conclusion

A trim optimisation study for an Aframax tanker vessel is reported in this paper, using a CFD software called the Naval Hydro Pack. In addition to the standard, calm sea trim optimisation study, an investigation of power and fuel savings is extended to irregular waves to assess the applicability of calm sea results to realistic operational conditions.

The study in calm seas showed that moderate savings can be achieved for the Aframax vessel, given the low speeds at which she sails. The fuel differences range from 0.2 to 1.0 tons per day. Larger differences in consumption are observed in the ballast condition due to the larger flexibility of the draft and trim. The investigation in waves showed that similar trends can be expected, at least when it comes to head waves. Moreover, the absolute values of saved fuel increase in waves comparing to calm sea.

For the specific ship considered in this study, it is estimated that around 44.2 tons of fuel per year can be saved, per ship. For a fleet of seven sister ships, this converts to a ROI of less than two months.

In general, it can be concluded that there is an economic benefit in performing trim optimisation studies for full hull forms, at least those sailing on longer routes. The study also indicates that for this particular vessel higher savings can be expected in head waves by using the same data sets obtained in calm seas.

References

GATIN, I.; VUKČEVIĆ, V.; JASAK, H. (2019), *Fully Automated CFD Analysis for Full-Scale Ship Hydrodynamics*, 4th HullPIC, Gubbio

HOGBEN, N.; DACUNHA, N.; OLIVER, G. (1967), *Global Wave Statistics*, Unwin Brothers, London

JASAK, H.; VUKČEVIĆ, V.; GATIN, I. (2015), *Numerical Simulation of Wave Loads on Static Offshore Structures*, CFD for Wind and Tidal Offshore Turbines, Springer Tracts in Mechanical Engineering, pp.95-105

JASAK, H.; VUKČEVIĆ, V.; GATIN, I.; LALOVIĆ, I. (2019), *CFD validation and grid sensitivity studies of full scale ship self propulsion*, Int. J. Naval Architecture and Ocean Engineering, pp.33-43

KISHEV, R.; GEORGIEV, S.; KIRILOVA, S.; MILANOV, E.; KYULEVCHELIEV, S. (2014), *Global View on Ship Trim Optimization*, 2nd Int. Symp. Naval Architecture and Maritime (INT-NAM), Istanbul. pp.223-234

VUKČEVIĆ, V.; JASAK, H. (2017), *Implementation of the Ghost Fluid Method for the Free Surface Flows in Polyhedral Finite Volume Framework*, Computers and Fluids 153, pp.1-19

Making Data Profitable

Falko Fritz, SkySails Marine Performance GmbH, Hamburg/Germany, falko.fritz@skysails.de

Abstract

Clever, condition-based hull cleaning intervals can reduce the fuel costs of cargo vessels by 5-10%. Particularly in times of rising fuel prices, this is a great advantage in a volatile and competitive market. However, hull condition monitoring or vessel performance management tools like SkySails V-PER are only effective when they enable employees to take informed decisions. In the end, it is their personal expertise that makes the profit. Developing a realistic, vessel specific picture of e.g. the fuel consumption curve over speed and other effects is not possible based on noon reports alone. It requires measurement data in higher resolution to identify cost saving opportunities and to make for instance condition-based hull cleaning schemes possible. To take effect, the analysis results must reach the right decision makers at the right point in time. This organizational process is the second and equally important pillar to create value from data.

1. Introduction

Hull condition monitoring and strategies to properly determine the hull cleaning intervals are a necessity in cargo shipping. Still, many ship owners rely on the analysis of noon report data to this day. Professional hull condition monitoring systems or vessel performance management systems in general are sometimes not in use at all or their results do not reach the intended goal. This paper looks at the causes of this problem and possible ways to solve it.

1.1. SkySails V-PER

SkySails V-PER is a vessel performance management system consisting of hard- and software to optimize the operation of cargo vessels. An industrial PC certified for maritime use sits at the core of the hardware. It is used to process the measurement data on board the vessel and communicate with the existing IT infrastructure. In the usual configuration, several measuring devices such as mass flow meters, other sensors and talkers via the existing nautical NMEA protocol are connected to it.

The V-PER software installed on board enables the crews to use the measurement data for their own optimization tasks and optionally for entering noon, arrival and departure reports. Data that cannot be recorded automatically, like e.g. type of cargo, Douglas sea state or the timestamps for beginning and end of sea passages are manually entered there.

All measured and manually entered data are then sent to an onshore database where they are stored persistently. From there, noon, arrival, departure and daily fleet overview reports are generated automatically and sent out to pre-defined email recipients. An online portal to access the data in real time is available, too. A team of experienced data analysts monitors the processes and generates monthly reports regarding hull and propeller degradation, charter warranties or main engine performance.

1.2 Customers' motivation

When investing in V-PER, the customer usually aims to reduce his fleet's fuel consumption first and foremost, or benefit from the data in other ways. The technical measurement values are merely a necessary step in a longer chain of data processing.

Optimizing the hull cleaning intervals, switching from a fixed time schedule to a condition-based planning process is one of the most profitable uses of data in vessel performance management. Practical experience shows that between 5 and 10% of the fuel costs can be saved realistically when a professional hull condition monitoring solution is employed properly, as stated by *DNV-GL (2017)*.

In addition, many customers have secondary goals, e.g. by positioning themselves in the market with above-average transparency, creating awareness for bunker consumption among their crews, using the structured data handling process as an argument for banks and investors, or sharing the data with research facilities for a joint development. The range of motivations is as diverse as the shipping market itself.

2. Establishing a Condition-Based Hull Cleaning Regime

The decision to establish a condition-based hull cleaning regime and to purchase a product like V-PER is usually taken by the management. In practice however, the expected results often do not show as intended within the first few months. At first, between purchasing the system and getting it fully operational, it does the exact opposite, it creates costs and requires personal resources instead of reducing and streamlining them.

2.1 Purchasing and Commissioning a Vessel Performance Management System

When customers buy V-PER, the first step is to negotiate a contract with SkySails, committing the customer to pay the purchase price and monthly fees in exchange for hardware, software and continuous reporting and maintenance services. After that, the technical teams get busy with installing and commissioning the equipment, while the crews get trained to use the software, Fig.1.

In this process, some important stakeholder groups are often left out of the loop, namely the operations or chartering team. But since they play a vital role in using the results and turning them into a profit, they must be taken on board as early as possible to work hand in hand with the fleet management on the hull condition monitoring.

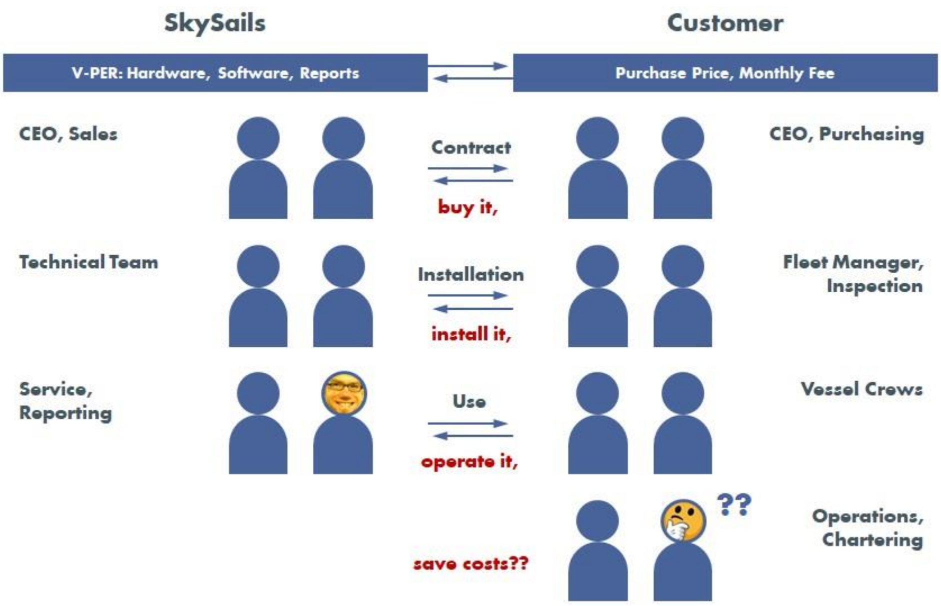


Fig.1: Communication during purchasing and commissioning process

2.2. Determine a Realistic Fuel Consumption Curve

Saving costs by optimizing hull cleaning intervals is a process that takes several months at least. The procedure laid out in ISO 19030 or any similar methods compare the in-service performance to a reference period after a dry-docking. This logically takes some time.

So before elaborating further on hull condition monitoring, other saving opportunities can take effect more quickly. Finding the ship speed that will return the maximal profit in any given market situation is a challenge that has become increasingly important since commercial shipping entered the turbulent waters after the financial crisis of 2008, with its strong fluctuations in charter rates, Fig.2, and even more so since the 0.5% global sulphur cap affected the bunker prices.

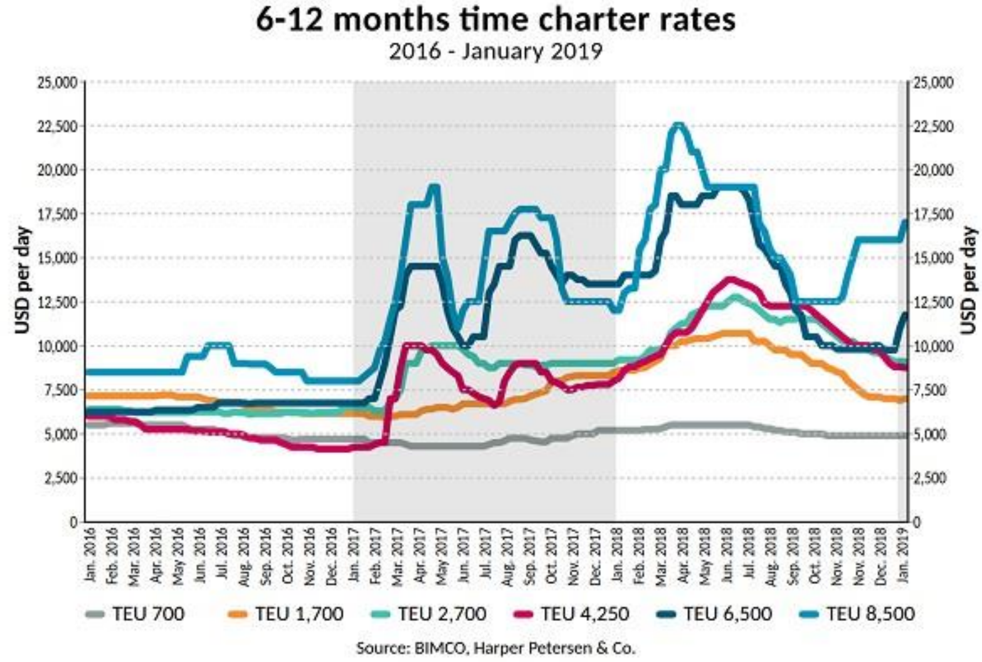


Fig.2: Charter rate fluctuations according to *BIMCO (2019)*

For reaching this target, operators require a realistic, up to date, vessel specific fuel consumption curve over ship speed. Many shipping companies still rely on noon report entries to achieve this. However, noon report entries summarizing the past 24h never show a detailed picture. Weather conditions change over a day, ship speed and consumption as well, and the results from analyzing noon reports systematically display large scatter. Fig.3 shows the 24h main engine fuel consumption rates (FCRme) and speeds over ground (SOG) reported for an exemplary vessel over three months.

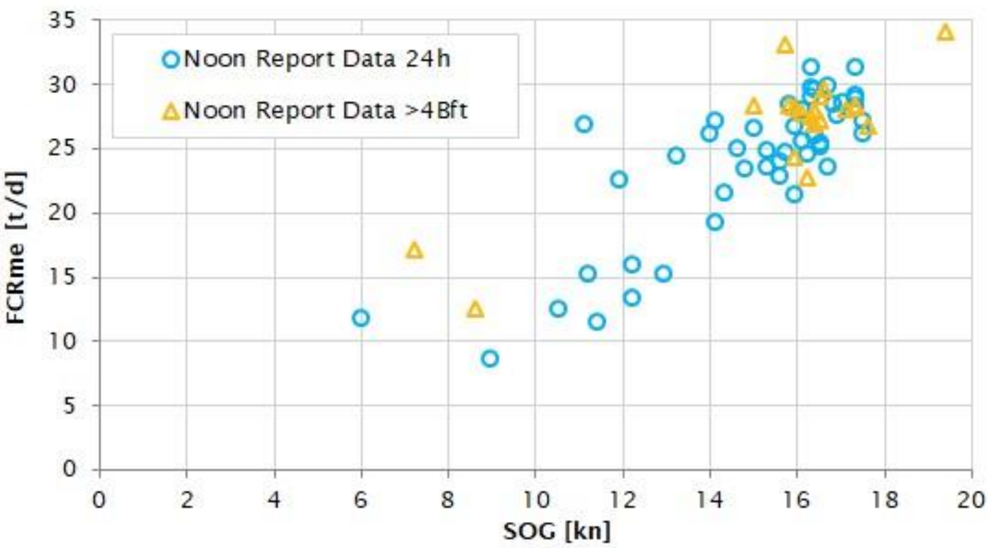


Fig.3: Main engine fuel consumption rate over ship speed from noon report entries

A clear consumption curve is hard to make out, particularly in the operationally important range of slow steaming. Even the differentiation between good weather conditions (0-4 Bft) and bad weather (5 Bft and above) does little to reduce the scatter.

The picture changes completely when measurement data are added, Fig.4. Each small dot in the diagram represents 10 minutes of operation, measured by Coriolis mass flow meters and recorded with V-PER. A fuel consumption curve is easy to approximate, and the effects of weather are clearer to make out, too.

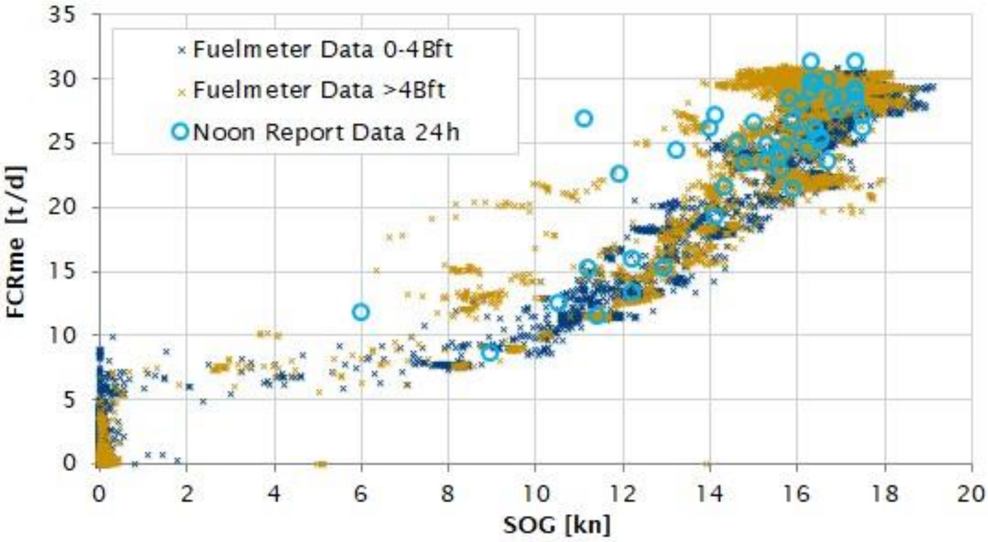


Fig.4: Main engine fuel consumption rate over ship speed measured with V-PER

For the further evaluation, only the 0-4 Bft data are used. Changes in sea state affects the ship resistance too much at 5-12 Bft and the required comparability of data points cannot be assumed. Using the filtered FCRme data as reference, it is easy to approximate a median curve and the 95% confidence interval, as shown in Fig.5.

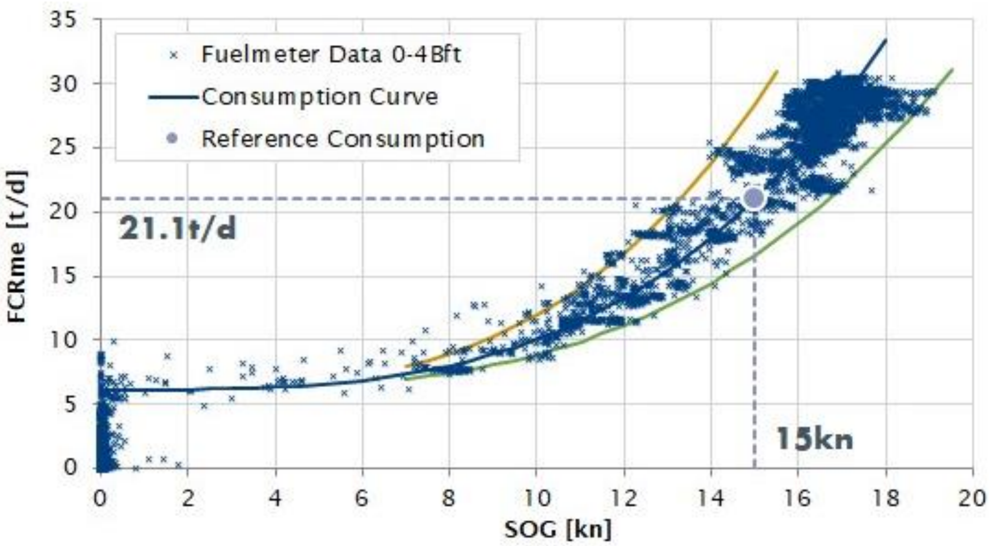


Fig.5: Approximated median consumption curve and 95% confidence interval

Getting a clearer image of the realistic vessel fuel consumption helps ship owners and operators to find the most profitable ship speed and position their vessel competitively on the charter market and limiting the risk for speed and consumption claims. This can be achieved within a few weeks after the commissioning of V-PER.

For hull condition monitoring, making data points comparable across a wide range of speeds is equally important. But for this purpose, other factors have to be considered, as discussed in the following chapters.

2.3. Surface currents

The ship speed shown in Fig.3 through Fig.5 is given as ship speed over ground (SOG). For determining transport efficiency, this is the relevant speed, since the sea passage is accomplished when the ship reaches the geographical position of the destination port.

For evaluating hydrodynamic effects however, speed through water (STW) is the relevant factor. Surface currents influence the attained SOG, which can be measured very precisely by tracking the GPS positions. STW on the other hand requires a precise speed log on board the vessel, which is often not available or questionable due to fouling or improper calibration. In some cases, the log offset is e.g. a linear function and can be corrected. Checking the consistency of the speed log and correcting it if possible is another function for which higher frequency measurement data are essential.

2.4. Center Draft

Besides speed and weather, the vessel draft has a significant influence on fuel consumption. Empirical data reveal this effect quite clearly, too, as Fig.6 shows. The diagram shows the correlation of the M/E fuel consumption rate normalized to reference speed (15 kn for the vessel in this example) over center draft. A linear approximation was added. With this, the reference conditions can be extended to also account for different drafts. For the vessel in the chosen example, the reference center draft is set to 10.5 m.

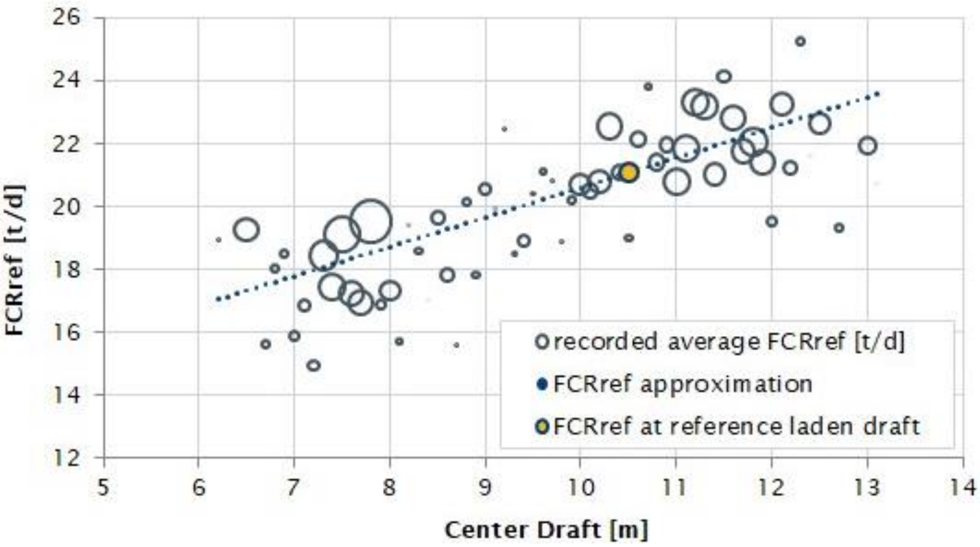


Fig.6: Exemplary effects of center draft on M/E fuel consumption rate at reference speed

2.5. Further influences: fuel quality, trim, water depth and sea state

With a vessel performance management system on board, the vessel crews are suited to play an active role in improving fuel economy. Some factors influencing the consumption can hardly be avoided, like e.g. fuel quality or squatting due to shallow water. Optimizing the vessel's trim and employing a reliable weather routing program on the other hand, are two factors that can be influenced by the crews while underway. These are additional benefits of V-PER but used independently of the hull condition monitoring.

2.6. V-PER Hull and Propeller Degradation Report

Taking the described influences into account, the V-PER Hull and Propeller Degradation report tracks the median M/E fuel consumption rate at reference conditions (FCRref) over time, see Fig.7. Each small dot in the graph represents the median value of FCRref for one day. In case of steadily increasing results compared to the baseline, hull fouling is the most reasonable explanation for this trend.

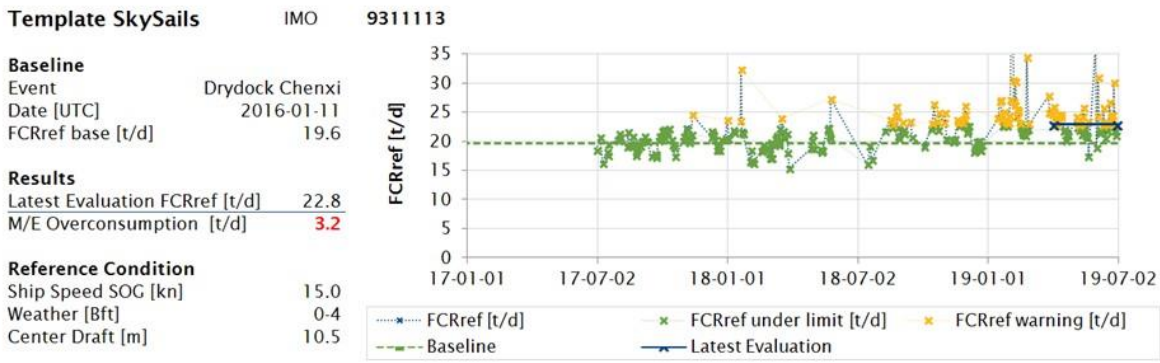


Fig.7: Anonymized results in the monthly V-PER Hull and Propeller Degradation Report

In contrast to the calculation method laid out in ISO 19030, V-PER uses the M/E fuel consumption rate as main indicator, rather than the delivered M/E power. In theory, changes on the main engine or its efficiency could result in a steady increase of the M/E fuel consumption, too. However, practical experiences show that this is rarely an issue. On the majority of vessels, the main engine is constantly checked by the chief engineer and the fleet management, who keep a keen eye on its condition. Problems with the main engine are usually detected before they show up as a long-term trend in the reporting. Using V-PER to display and communicate e.g. exhaust gas temperatures or regularly performing a cylinder pressure measurement can help to improve this. In practice, the correlation of M/E power and M/E fuel consumption rate is often almost perfectly linear, and it stays that way over years.

For this reason, omitting torque meters in the favor of fuel mass flow meters is a step to reduce hardware costs while keeping the main goal in focus, namely improving the profitability of the fleet. Fuel meters can substitute torque meters reasonably well, and they measure the substance shipping companies actually pay for, the bunker oil.

When the overconsumption reaches quantities like in the example in Fig.7, several tons per day, the benefit of a hull cleaning becomes evident very quickly. Even if only half of the overconsumption can be reduced by the cleaning, 1.6t/day less consumption means 16,000US$ savings every month at a fuel price of 500US$/t and 20 days at sea per month. The opposite result, realizing that a vessel does not need a hull cleaning for the time being, saves the immediate cleaning costs and helps to prolong the lifetime of the anti-fouling paint.

With this, the 5-10% savings achieved by improving vessel condition as stated by *DNV-GL (2017)*, seem very realistic. The savings suffice to not only pay for the cleaning within a few weeks, but for the vessel performance management system as well, even on the comparatively small vessel in the example, due to this effect alone.

3. Goal-oriented Communication

The success of vessel performance management systems is dependent on the people who use them and employ the results in their decision making. Different teams in the customer's organization require different evaluations to support their specific work. Providing these to the right people at the right point in time is vital for realizing the full benefit.

For this communication structure, there is no general blueprint. Organizations differ and the individual customer's needs must be accounted for by adapting the information flow and by customizing the reporting. The importance of this aspect is often underestimated in practice. Consequently, the manufacturers of solutions like V-PER must keep an extra keen eye on this topic during the whole process. Then, the information provided can become an integral part of the communication within the organization, as well as between the customer and SkySails, Fig.8.

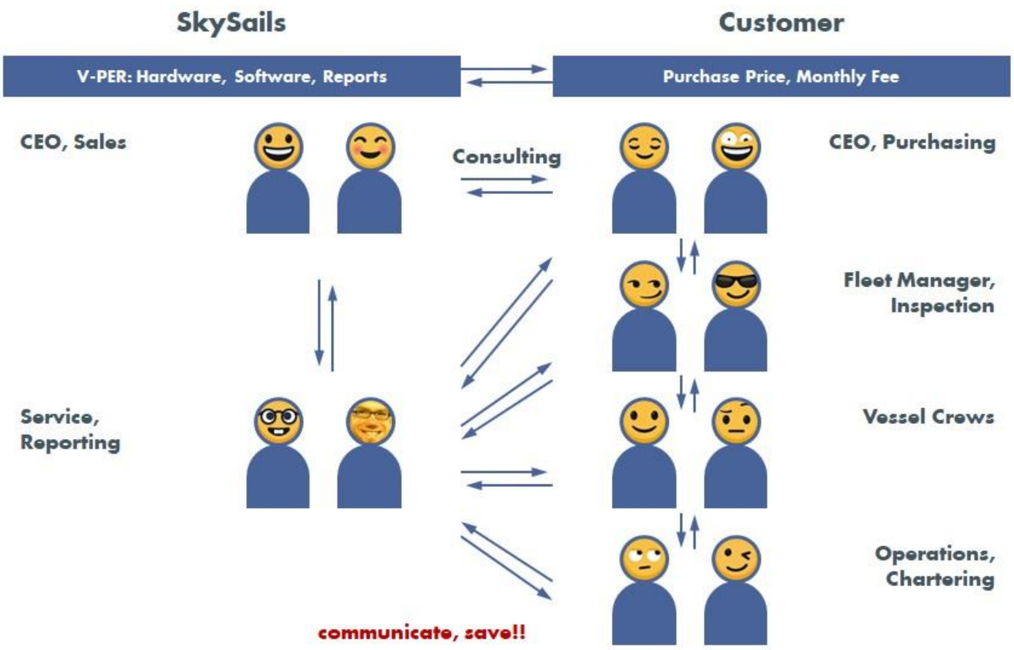


Fig.8: Communication in full operation

4. Conclusion

The widespread availability of sensors, data exchange and analysis algorithms should not conceal the fact that at the end of the information chain, there is a person who takes a business decision. The acceptance of analysis results in daily business is a vital step to optimize the fleet performance and succeed in a volatile and competitive market. Only with this final link to the business side of the organization, vessel performance management solutions reach their intended goals. Therefore, systems like V-PER are always a product and a process in combination.

Particularly at the start, close communication between the supplier and the customer is required. Practical experience shows that these efforts pay out quickly even if only some of the benefits of such a system can be utilized effectively. Hull condition monitoring is often one of the most powerful tools to reduce fuel costs. However, this cannot be achieved by evaluating noon report data only. Noon report data are not sufficient to derive the required normalization functions and make data comparable over years and across all the differing operational conditions vessels encounter. Only higher frequency data can provide the data quality that is necessary to give reliable recommendations on hull cleaning intervals and other efficiency related topics.

Then, goal-oriented communication is just the one last step on the way towards lean, fact-based decision-making processes in daily business, in order to advance and create value from data.

References

DNV-GL (2017), *How to achieve energy efficiency excellence*, https://www.dnvgl.com/article/how-to-achieve-energy-efficiency-excellence-102139

BIMCO (2019), *Container Shipping: The Many Pitfalls in the Coming Months Will Decide the Fate of the Year*, https://www.bimco.org/news/market_analysis/2019/20190219_2019_01_container_shipping

Engine Condition Monitoring based on Specific Fuel Oil Consumption Observation over Time

Wojciech Górski, Enamor Ltd., Gdynia/Poland, wojciech.gorski@enamor.pl
Jerzy Michniewicz, Enamor Ltd., Gdynia/Poland, jerzy.michniewicz@enamor.pl
Agnieszka Szlendak, Enamor Ltd., Gdynia/Poland, agnieszka.szlendak@enamor.pl

Abstract

The purpose of the study was to examine the possibility of using collected data to monitor marine diesel engine condition. As engine condition can be expressed by its energy efficiency, the tool is based on specific fuel oil consumption observation over time. The major aim of tool development process, was to narrow down data scatter, to enable derivation of reliable trend line. Additional challenge was to assure the availability of fuel calorific value and ambient parameters used for correction to ISO standard conditions. A sensitivity analysis was performed, in order to determine their influence on SFOC trend. The results identified a strong dependency on the availability of key parameters, resulting in high dispersion in case correction to ISO conditions is not possible. Therefore, an idea of predicting most important parameters was investigated. Different approaches were elaborated to build useful predictive models, including use of data not collected onboard. Study was performed for ship main engine and proved to be useful in planning of maintenance activities.

1. Introduction

Vessel can be seen as a complex structure of mutual interactions among its subsystems and modules which condition can be described by data. Nowadays these data are much wider available since modern vessels are equipped with sensors providing continuous monitoring capability. Data availability creates opportunity for quantifying vessel performance and better understanding of its influencing factors. Knowledge built based on data allows therefore for maintaining long-term vessel efficiency.

Taking advantage of data availability is only possible with use of data collection system capable of interfacing multiple data sources of different standards, structure and context. Low level of onboard equipment standardisation imposes demand for flexibility of data collection system. Beside of data collected onboard the vessel it is often helpful to expand dataset with additional information such as weather conditions provided by specialised services. Additional data provide redundancy and may be used whenever data collected onboard are missing or cannot be trusted.

SeaPerformer™ developed by Enamor within the scope of research project sponsored by National Centre for Research and Development is an example of data collection system capable of gathering data of different sources and formats. Its flexible and modular structure allows for interfacing variety of systems and sensors creating comprehensive database which can be further expanded with trusted weather services available through partnership with metocean expert company Tidetech.

System provides number of tools for assessment of vessel performance both on general level and with reference to its vital subsystems. This study focuses on combustion engine efficiency monitoring in the time domain in order to predict trends in condition deterioration and spotting anomalies. Although SeaPerformer™ is capable of collecting detailed information of engine operational condition this study is based on extremely narrow dataset i.e. engine load and fuel consumption with limited engine ambient conditions. Data scatter and inaccessibility is also addressed in this research in order to demonstrate robustness in processing incomplete information.

2. Method

To monitor engine condition, specific fuel oil consumption (SFOC) observation over time has been chosen. In order to employ the method independently of engine load, SFOC curve against engine load is considered as the reference model.

Signals acquired from sensors are sampled at least once per minute depending on source and all averaged to 1-minute signals. Actual fuel calorific value is reported by the crew on the basis of laboratory results, in a form of manual inputs typically updated once a day. Relevant sources of signals are presented in Table I.

Table I: Required signals

	Signal	Source
P_B	Brake power of main engine	ETM - optical torquemeter
$\dot{m}$	Fuel mass flow by fuel type	EFCM - fuel consumption monitoring system
LCV	Lower calorific value by fuel type	SeaPerformer™ - Manual Inputs module
t_{sc}	Engine charge air coolant temp.	
t_a	Engine intake air temperature	Engine Monitoring/Control System
p_a	Engine intake air pressure	

Specific fuel oil consumption at ambient conditions is calculated as:

$$SFOC_{meas} = \frac{\dot{m}}{P_B}\left[\frac{g}{kWh}\right].$$

To enable a comparison of fuel amounts consumed in different conditions, a two-step correction is required. First, SFOC calculated for calorific value of different fuel types and certain bunker supplies is normalised with common reference of LCV_{ref} = 42700 [kJ/kg]. Then, it is corrected to standard reference conditions given in *ISO15550-1 (2016)*, according to a procedure laid down in engine project guide, *MAN B&W (2014)*, as advised in *ISO3046-1 (2002)*. Applying both corrections results in:

$$SFOC_{std} = \frac{LCV}{LCV_{ref}} \cdot \frac{SFOC_{meas}}{\beta}.$$

The β parameter is calculated as:

$$\beta = 1 + c_1 \cdot (t_{sc,meas} - t_{sc,std}) + c_2 \cdot (t_{a,meas} - t_{a,std}) + c_3 \cdot (p_{a,std} - p_{a,meas})$$

where c_n are engine type specific coefficients. Standard reference conditions are subscripted with *std*, and measured ambient conditions with *meas* respectively. For long-term trending the difference between standardised and reference SFOC serves as engine performance indicator:

$$\Delta SFOC = SFOC_{std} - SFOC_{ref}.$$

Fuel consumption reference model is built as a function of engine load, on a number of operating points valid for engine's initial condition. Building a reference on a basis of data collected in regular operation requires complex filtering, *Trodden et al. (2015)*. The initial state could be found for the new engine tested on site or derived from data measured on-board on the beginning of ship operation, e.g. sea trials. For a company not directly involved in design and ship building process, it is sometimes a struggle to acquire accurate data for modelling purposes. In order to determine the most reliable source of reference data for 1700 TEU class vessels, two available sources were compared visually against actual data registered onboard. The first reference data set comes from engine's workshop acceptance tests. The other one is engine type specific reference. Reportedly, it originates from engine manufacturer after consumption optimisation to a different load range was performed. On Fig.1 original reference datasets are presented, interpolated with cubic splines. Equal efficiency degradation over the power range was assumed. Hence, both curves were moved vertically to fit the measured consumption data with use of least squares method.

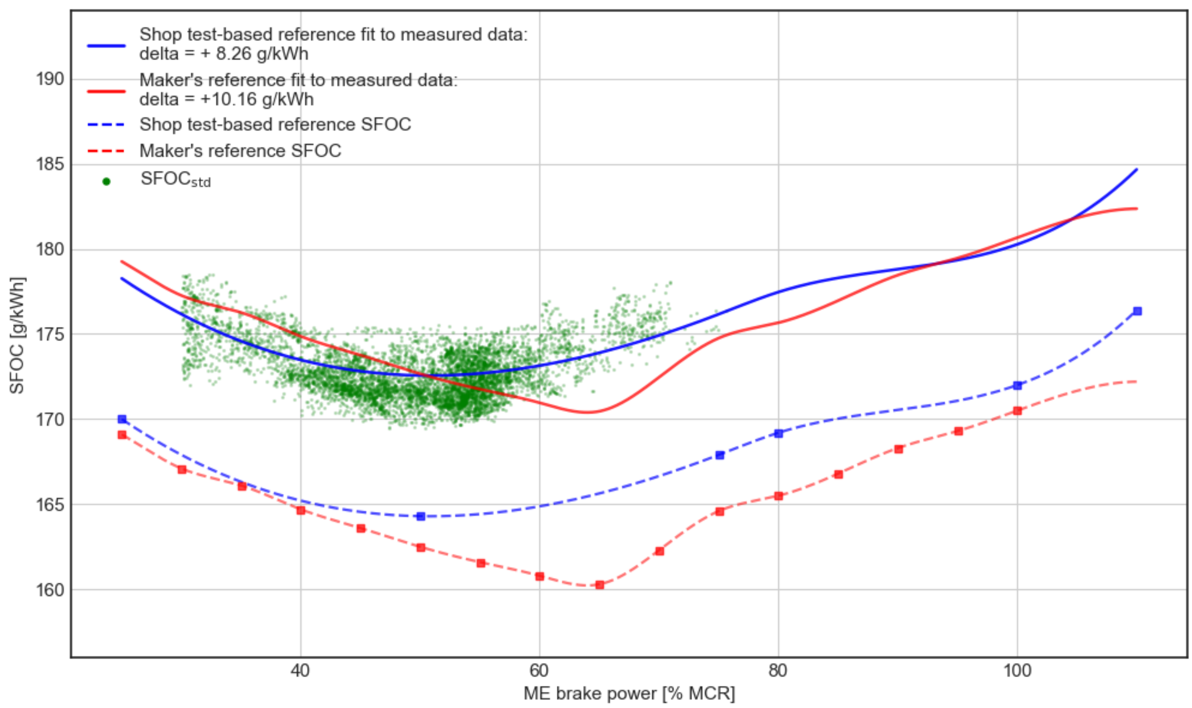


Fig.1: Fitting best reference model

Although the measured points only span over the range of 30-75% load, it is clear that shop test based reference model represents the shape of registered data more precisely than the generic model. The major drawback of shop test results is often the low number of load points at which measurements are taken. In this example, the mostly operated region of 40-60% MCR is described with one point only.

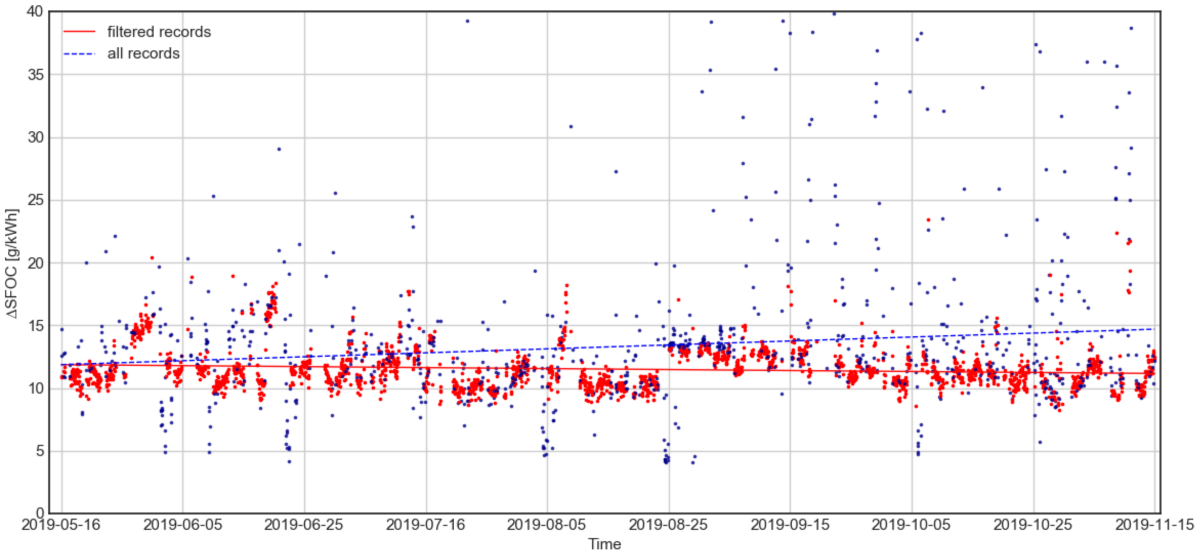


Fig. 2: Linear trend set on filtered and unfiltered data set

Change detection in engine performance is only possible with accurate data filtering. Appropriate filter passes through the possibly wide data set, yet consisting of valid data points only. Employed filtering mechanism is based on physical conditions and statistical tools. It consists of 3 stages. First, unsteady states of ME operation are filtered out. Because of long term character of the analysis, all variables are averaged to 1-hour samples. Within every averaged sample relative standard deviation (RSD) of ME brake power shall be kept below 0.04 [-]. The value has been set experimentally. Initially RSD = 0.03 was considered. This value corresponds to approximately 3 r/min of engine rotational speed standard deviation limit given in *ISO 19030-2 (2016)*, assuming the speed of 100 r/min. Finally, it has been decided to control RSD of brake power instead of rotational speed, because the latter is kept constant during engine operation. The second filter cuts off records with ΔSFOC outside the range of (-30, 50) g/kWh to roughly clean the dataset before the last stage. The third filtering stage cleans out outliers, based on interquartile range (IQR) idea. However instead of using quartile- (4-quantile), tercile range (3-quantile) has been used to make the filter little more restrictive. Fig.2 shows an example dataset with indicated points which passed through all three filters. Linear regression demonstrates the influence of filtering on trending.

3. Ensuring appropriate data availability

The challenging part of the analysis is to provide the complete and reliable signals, representing possibly wide set of engine operation states. Lacking data from a single instrument may occur when it is turned off or in case of failure. Signals fetched indirectly, through Alarm and Monitoring System (AMS) may be subject to AMS reconfiguration which also may lead to gaps in dataset. The lacking correction parameters' values may be replaced with default values, given in EU MRV regulation, *EU (2015)* and *ISO15550-1 (2016)* respectively. However, sensitivity analysis showed, that such assumption may lead to significant discrepancies in $SFOC_{std}$. In a typical case, where $SFOC_{act}$ is 170 g/kWh, possible LCV span of 1000 kJ/kg results in about 4 g/kWh difference in $SFOC_{std}$. Similarly, resulting $SFOC_{std}$ differences were derived for min./max. values of the other correction parameters, registered on selected vessels' operation. All these values, presented in Table II indicate correction parameters' influence on the result.

Table II: Influence of correction parameters on SFOC

Correction parameter	Min value	Max value	Difference in $SFOC_{std}$ [g/kWh]
Lower calorific value [kJ/kg]	42200	43200	4.1
ME charge air coolant temperature [°C]	27.8	39.1	1.1
ME air intake temperature [°C]	19.0	44.0	0.9
ME air intake pressure [hPa]	1000	1042	0.2

As Table 2 shows, the most important correction parameter is LCV. Because it comes from crew's manual inputs, it is prone to human errors and negligence. In order to ensure data reliability, validation of entered data is implemented in user interface. SeaPerformer^{TM} makes it in two ways. First, entered LCV value is checked roughly against the allowed range, specific for a certain fuel type. The ranges are defined with an arbitrary margin around the type specific default values. The second step is based on the reference to a certain fuel supply. If the bunkering of specific fuel type is reported including its mass and calorific value and the crew keeps using fuel of the oldest delivery, system validates the entered value against the LCV of presumed supply. Unfortunately, for some bunkering operations calorific value is not determined, which results in empty fields in database and leads to use of default values explicitly. Calorific value of the fuel being consumed also may differ from the one of the bunkered fuel, depending e.g. on fuel oil separators and heaters operation.

In order to provide all values in full time domain, environmental parameters of SFOC correction to ISO conditions may be modelled to avoid the use of default value. According to sensitivity analysis, charge air coolant temperature was identified as the second most influential parameter, hence it has been chosen for building a predictive model. Simple linear regression has been implemented which leads to a formula of $t_{sc} = c_1 \cdot x_1 + c_2 \cdot x_2 + \cdots + c_n$. This approach allows to clearly identify the influence each variable has on the prediction.

Series of three 2500 TEU class container ships was selected, where instead of charge air cooling water temperature, air temperature after cooler is measured. Data from other two container vessels with both signals measured show that average difference in temperature between air on cooler outlet and water on cooler inlet is 4.3°C. Hence this constant value was subtracted from the model output.

First step was to determine variables influencing charge air temperature in order to put them into a model. Focus was kept on one selected ship. Both forward and backward selection on all available variables was performed. This method tries and evaluates the model with different sets of variables and returns the best combination. After confronting its results with own expertise, a promising set of features were recognised. Those features were worked out into a model. It was also decided to get rid of rarely available scavenge air receiver pressure. This way much bigger dataset was obtained enabling to create an optimal model that could be used with minimum amount of existing data. There was an attempt to delete cooling sea water inlet temperature [°C] as well, but it turned out to significantly reduce model accuracy. Therefore, it was agreed to keep it among selected features presented in Table III. Measured data preparation consisted of averaging to 15-minute samples and removal of outliers.

Table III: Signals selected as model inputs

Signal	Source
Main engine load [% MCR]	ETM torquemeter
Main engine rotational speed [r/min]	ETM torquemeter
Cooling sea water inlet temp [°C]	Alarm and Monitoring System
Sea water temperature [°C]	Weather service

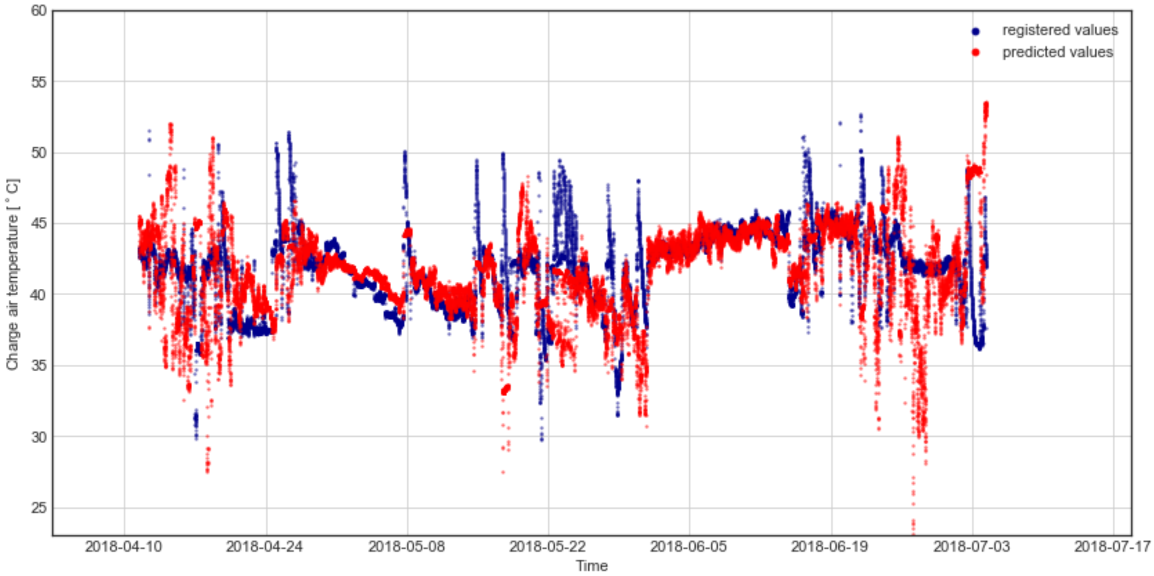


Fig.3: Registered and predicted values of modelled variable over time (tuned and predicted for a single ship)

On the first model coefficient of determination $R^2 = 0.90$ has been achieved. R^2 measures the goodness-of-fit of the predictive model, where $R^2 = 1$ means perfect representation. With those results in mind we decided to broaden our scope of interest and tried to create one model that will suit a series of four 2500 TEU class ships. The same optimal set of variables was used to observe how the accuracy of the model would change.

This time much wider time frame was selected- there is only a part presented on Fig.4. As a result, there of course was a bigger variation in data, but despite this still considerably high R^2 equal to 0.68 was received. On Fig. 4 we can clearly see how predicted datapoints follow the patterns in original data.

Fig.5 shows the final model used for the same ship as in the first attempt. In extreme situations results are shifted down, by less than 5 °C. Having the model implemented it is possible to eliminate the use of charge air temperature default value (25°C). ΔSFOC mean value decreases as expected, by about 1.1 g/kWh when predicted temperature is used. However, no significant influence on dispersion has been observed on a population of nine ships of 1700 and 2500 TEU classes.

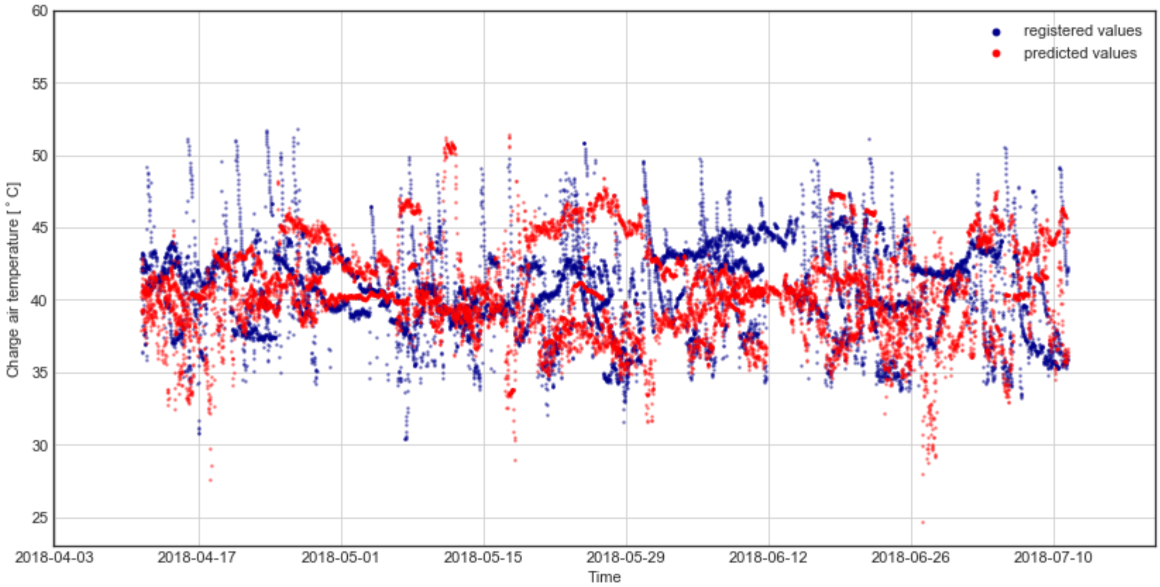


Fig. 4: Registered and predicted values of modeled variable over time (tuned and predicted for a series of ships)

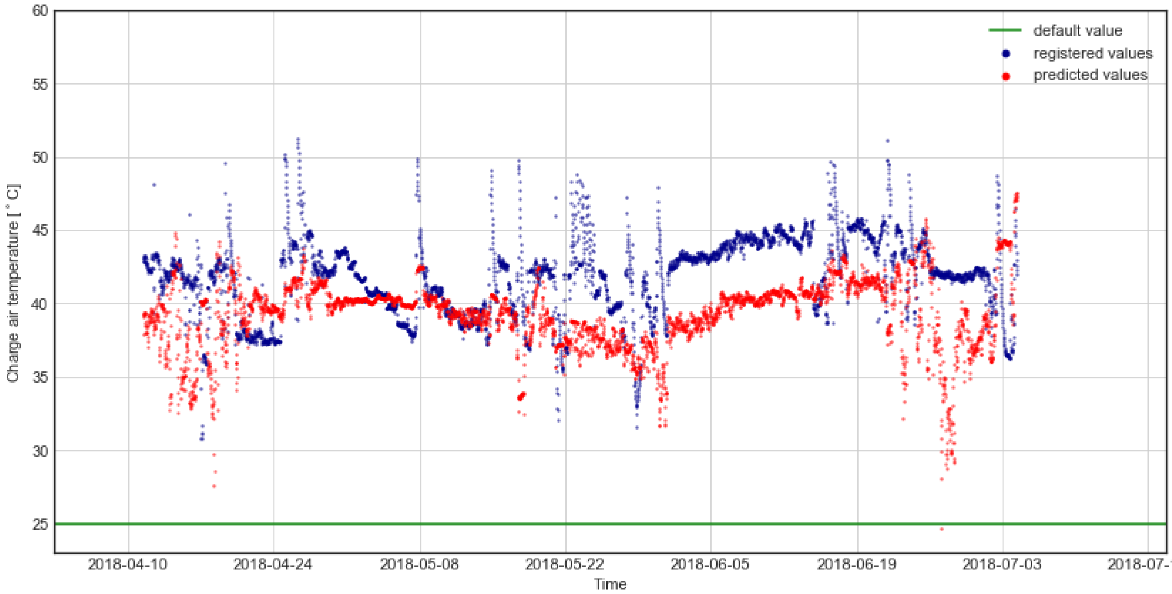


Fig.5: Registered and predicted values of modeled variable over time (tuned for the series, predicted for a single ship)

4. Results

Fig.6 demonstrates the resulting ΔSFOC scatter plot on 1700 TEU class ship. Provided the data are available without long gaps, it is possible to set an unambiguous trend on ΔSFOC despite scatter of about 5 g/kWh. On several ships, significant step changes in time were observed in the filtered values of ΔSFOC. However, physical meaning interpretation of the changes is difficult, because many factors influence the result. On one hand, it takes time for each anomaly to be observable on a long-term trend. On the other, the passing time complicates identification of causing events. Also, crews which can be interviewed to find the reasons are being changed or tend to forget. Possible reasons for step changes in specific fuel consumption are e.g. unrecorded significant change in LCV, flowmeter malfunction or unnoticed fuel valve switch, engine monitoring sensors malfunction or recalibration, engine-specific malfunctions, etc.

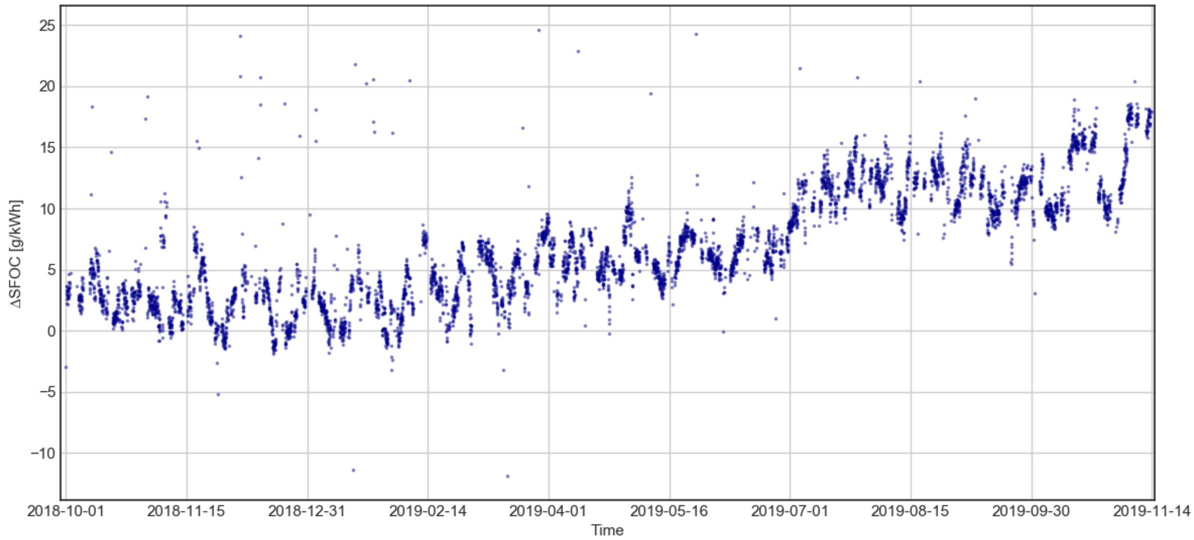


Fig. 6: One-year ΔSFOC calculated for a container ship

On each vessel similar "saw tooth" pattern occurs, visible as well on Fig.6. It appeared to associate with geographical location. Because the pattern repeats every voyage over long time and the effect is observable on many ships, it was assumed that influence of heavy weather conditions, changes in fuel characteristics, or single failures can be neglected. With geographical position both intake air and sea water temperatures are correlated and affect the engine thermal efficiency. Although their influence should be already reduced, these findings imply that the applied correction method may be insufficient. Fig.7 presents the part of operation of the same vessel as on Fig.6.

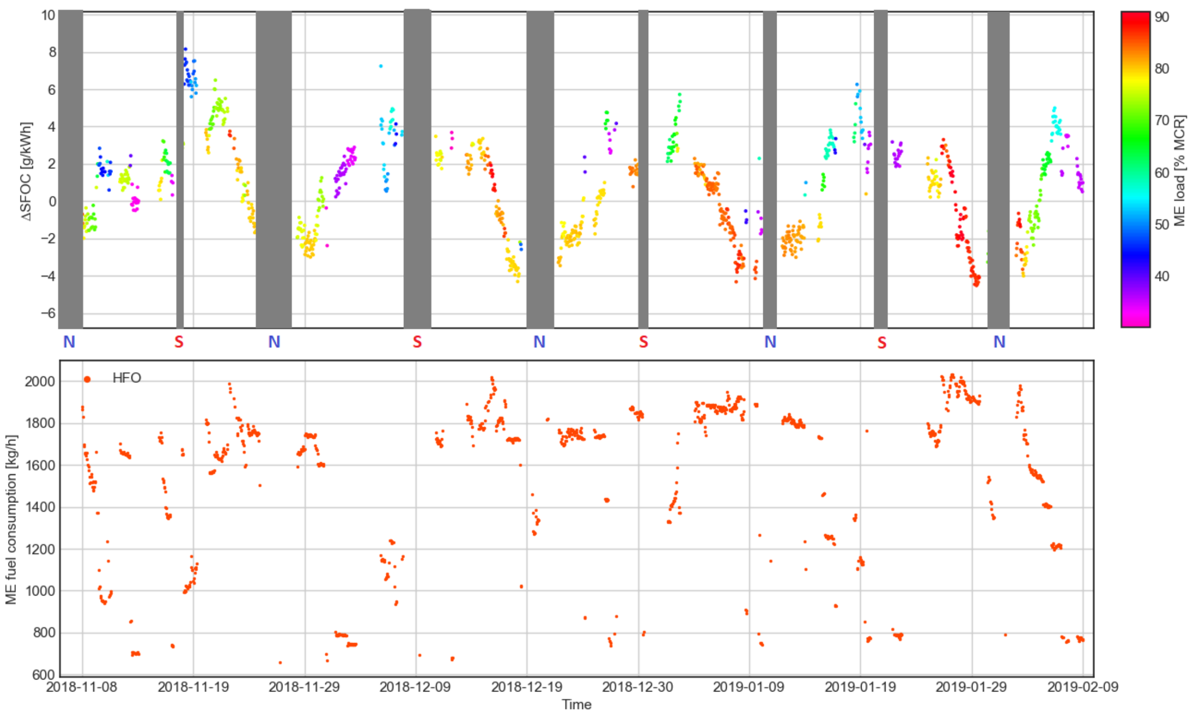


Fig.7: ΔSFOC over particular voyages between two groups of ports: N and S

The vessel sailed between northern (N) ports grouped around Korean Peninsula and southern (S) group of ports on the Gulf of Thailand. Visits in both regions were indicated in grey. The graph shows differences in ΔSFOC up to 12 g/kWh. Differences in average temperatures between both regions at the end of December are significant - about 20-25°C for air and about 20°C for sea water respectively, depending on a detailed location. It may be inferred, that lower ambient temperatures reduce charge air temperature and hence increase engine's thermal efficiency. Additionally, there is no influence of ME load, fuel consumption level, nor used fuel type on the observable pattern. However, it should be noted that water temperature has no direct effect on charge air temperature and engine intake air temperature is influenced by temperature inside engine room.

5. Conclusions

Sufficient filtering level has been achieved, which allows to set unambiguous trends on the obtained scatter points. However, the proposed algorithm must be fed with reliable correction parameters. Fuel calorific value highly influences the results and it is difficult to assure its availability. Modelling of lacking environmental parameters is possible and sufficiently precise to replace the standard default values.

The presented method may be used both for engine performance monitoring and fault detection. However, trend interpretation may require a person directly involved in ship operation, who combines interest in engine performance with actual information about main engine and its systems maintenance and fuel management. This could be chief engineer, superintendent or a fleet performance manager with in-depth knowledge of systems installed on the vessel.

Correlation between geographical position and SFOC has been identified among investigated fleet. Although the physical meaning of the pattern is not clear, the mere fact of occurrence of the fluctuations strongly correlated with weather parameters can motivate to look further for scatter reducing techniques.

Acknowledgements

The studies were carried out within the research project POIR.01.01.01-00-0933/15 co-financed by Polish National Centre for Research and Development.

References

EU (2015), *Regulation (EU) 2015/757 of the European Parliament and of the council of 29 April 2015 on the monitoring, reporting and verification of carbon dioxide emissions from maritime transport, and amending Directive 2009/16/EC*, Official Journal of the European Union

ISO 3046-1 (2002), *Reciprocating internal combustion engines – Performance – Part 1: Declarations of power, fuel and lubricating oil consumptions, and test methods – additional requirements for engines for general use*, International Standard Org., Geneva

ISO 15550-1 (2016), *Internal combustion engines - Determination and method for the measurement of engine power - General requirements*, International Standard Org., Geneva

ISO 19030-2 (2016), *Ships and marine technology - Measurement of changes in hull and propeller performance - Part 2: Default method*, International Standard Org., Geneva

MAN B&W (2014), *S60ME-B8.3-TII Project Guide. Electronically Controlled Two-stroke Engines with Camshaft Controlled Exhaust Valves*, Edition 0.5

TRODDEN, D.; MURPHY, A.J.; PAZOUKI, K.; SARGEANT, J. (2015), *Fuel usage data analysis for efficient shipping operations*, Ocean Engineering 110, pp.75-84

In-Transit Cleaning of Hulls

Rune Freyer, Shipshave AS, Stavanger/Norway, rune.freyer@shipshave.no
Eirik Eide, Shipshave AS, Stavanger/Norway, eirik.eide@shipshave.no

Abstract

A new method allows In-Transit Cleaning of Hulls (ITCH) by "grooming". ITCH at commercial speeds avoids the need of idling vessels in harbor for cleaning operations. The effluents from the cleaning operations with ITCH are disposed in deep waters offshore, with an objective of avoiding costal pest invasions. The ITCH method has been successfully tested on vessels with speed of between 9 and 14.5 knots at sea. The paper will discuss the learnings from the initial tests. The overall objectives of the ITCH are to clean the hull while maintaining the vessel schedule, to have very low costs per hull cleaning and to avoid damages to the hull paint.

1. Introduction to In-Transit Cleaning of Hulls

The commercial motivation for cleaning vessel hulls under water is to reduce the fuel consumption related costs, which is a large part of the total operating costs of commercial vessels. The hydrodynamic surface roughness caused by biofouling is reduced, and the viscous resistance is lowered. The environmental motivations are to avoid transport of invasive species and reduce greenhouse gas emissions due to a lower fuel consumption.

The cleaning methods has traditionally involved divers or dry docking, but underwater cleaning techniques are nowadays much more common due to the lower cost and shorter off-hire durations. Some challenges with the methods are:

- Off-hire time of vessel because
  - travel to port with cleaning facilities or to a cleaning location
  - waiting for cleaning and the cleaning operation
- Disruption of the schedule of the vessel causing cleaning to be deferred
- Rough methods degrade the antifouling paint, increasing marine growth for the future
- Low-cost In-Port Hull Cleaning treatments disperse waste such as invasive species and antifouling residue

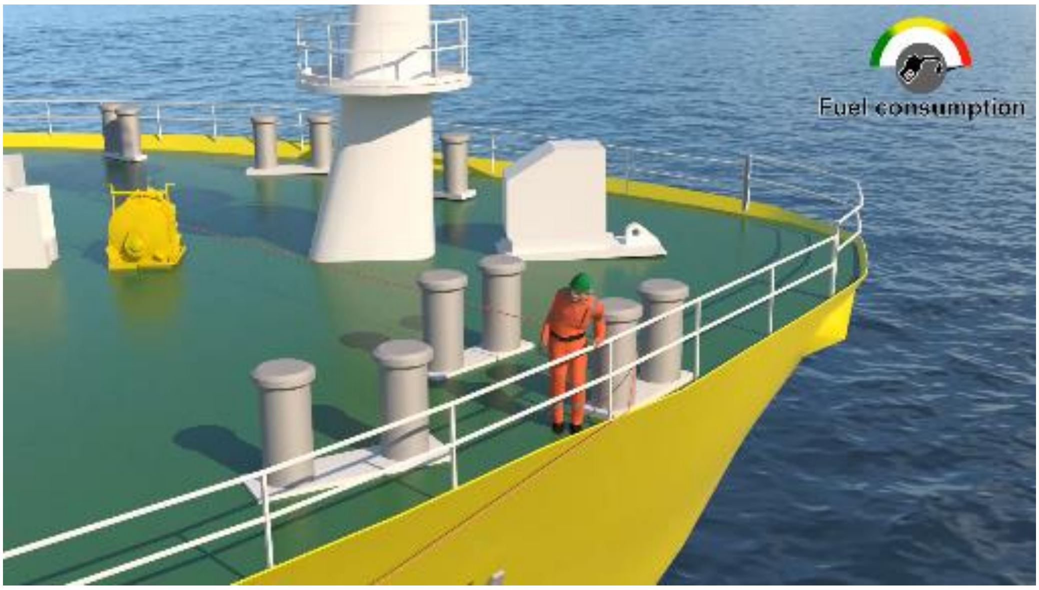


Fig.1: Winch on forecastle deck with rope via fairlead

As an alternative to in-port cleaning, frequent brushing with low forces were attempted (grooming), *Hunsucker et al. (2019)*. Grooming provides a superior surface, however, limited commercial popularity may be caused by the logistics of frequent treatments. To overcome these challenges, the ITCH system was developed.

2. In-Transit Cleaning of Hulls

Except for port calls for cargo operations and fueling, a ship is an independent unit. Crews takes pride in maintaining and running the ship uninterrupted and in shipshape. Traditional hull cleaning does not allow the crew to maintain the underwater hull. It has been performed by third-party specialists.

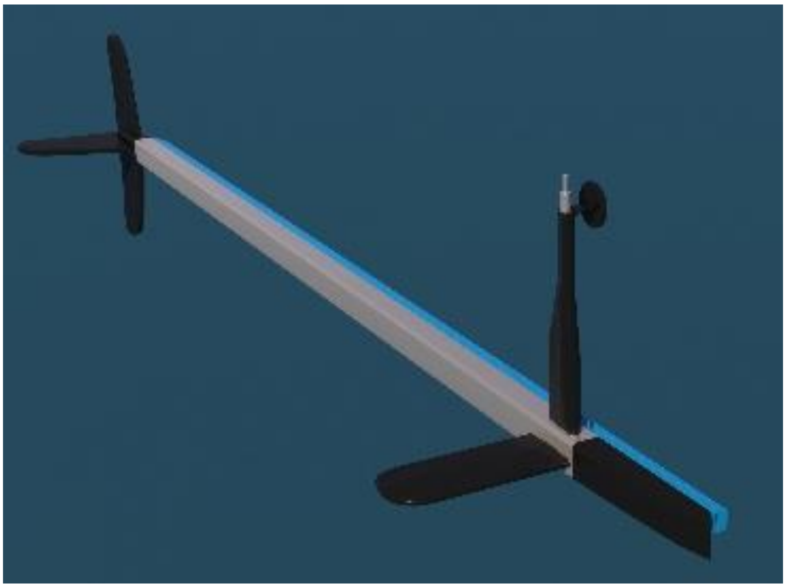


Fig.2: ITCH robot

The ITCH solution shall enable the crew to gain control over hull performance. The equipment required to be installed onboard is a winch on the forecastle deck. The robotic ITCH unit has a low mass and is hydrodynamically efficient designed, enabling easy manual deployment. The rope is led out via one of the foremost fairleads together with a robotic ITCH unit. The robotic ITCH unit has a rudder to maneuver and use the energy of the waterflow around the vessel to clean the hull. The robot automatically senses its position and conducts a vertical movement up and down on the hull sides while soft brushes are forced against the hull. The number of sweeps on each location can be defined through the combined settings of the winch and the settings on the ITCH Robot software.

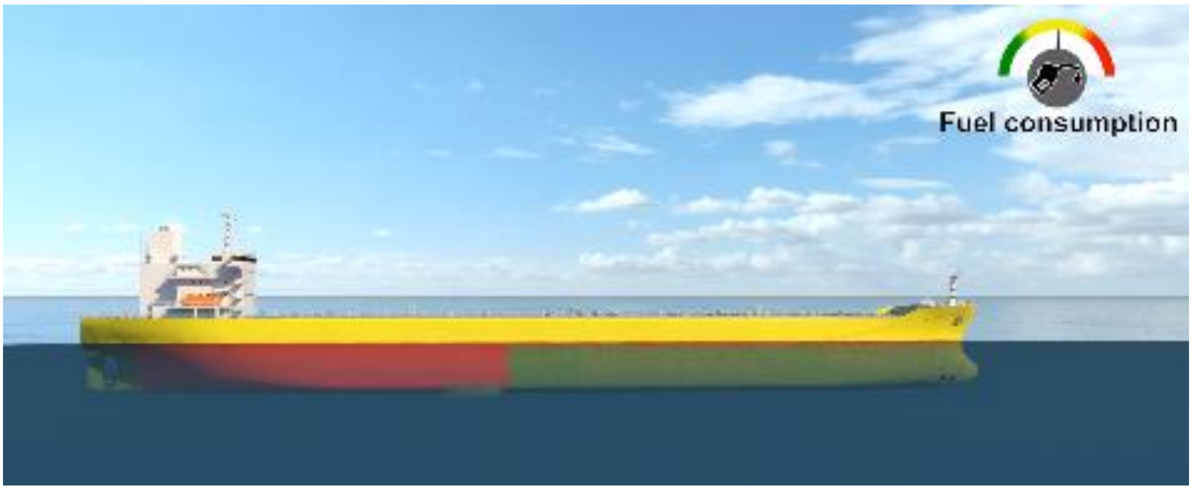


Fig.3: The robot is pulled forward by the winch in an overlapping pattern

The method uses non-rotating, soft brushes in a swiping motion with controlled hydraulic forces and a controlled number of strokes. A camera is attached to the ITCH Robot and can visually display videos with the effects of cleaning and the condition of the hull.

3. Hull performance measurement

The ITCH method is performed within a few hours at the same voyage. The ship has the same cargo condition and trim and usually similar weather and sea state. Measurements of fuel efficiency before and after cleaning on the same voyage will be unaffected by difference in loading and trim. The measurements will marginally be affected by currents and weather.

Hull performance depends on numerous variables and is difficult to measure and allocate to each individual source accurately. Hull paint roughness, fouling on hull and propeller, cargo loading, trim, sea temperature, current, wind, waves and speed through water all affects the apparent hull performance. Analyzing the data scatter accurately before and after hull cleaning requires advanced sensors and capable engineers to compensate for data noise. Hence the width of the data scatter may often be larger than the performance improvement.

The most accurate measurement of fuel efficiency improvement gained by a cleaning treatment will therefore be performed when cargo, wind, current, water temperature is the same and without delay. The simplest measurement with high accuracy of the hull performance effect of cleaning is made before and after an infinitely short treatment during a voyage. Cleaning in-transit can therefore negate the traditional long time series to get reliable estimates for fuel efficiency improvements.

4. Hull condition inspection

Many researchers advocate visual monitoring of hulls before cleaning to minimize paint wear and cleaning cost. The hull may be inspected by divers or ROVs to determine the need for an in-port cleaning operation. Qualitative information can be had, but quantitative is hard to get accurate as it depends on light, diver training, and other factors. The ITCH system may exhibit a cleaning cost for a hull that is lower than the survey cost. The soft brushes will likely eliminate paint cleaning damage. With a low-cost, neglectable damage cleaning method, inspections with high relative cost may provide less value.

Furthermore, the ITCH system has a video camera showing the cleaned surface before, during and after cleaning on the same screen picture. Because of the rapid flow during transit, released biofouling plumes may be seen, but the vision is unimpaired. One does not only get a regular hull cleaning, but also a regular hull inspection.

5. Invasive species and antifouling disposal

Hull fouling leads to the transportation of invasive species. Cleaning in port, dock or slipways contributes to such pests when ships are cleaned without complete capture and destruction of effluent. The antifouling polymeric components and its included biocides may also be released to accumulate in harbor sediments. IMO and others target to develop global regulations to avoid geographic variations to protect near shore aquatic environments. Researchers also point to the technical complexity of full effluent capture of in-port cleaning systems. From an environmental perspective, hull cleanings should be performed at locations where pollution and pest cannot spread, such as well controlled dry docks or the open ocean.

6. Cleaning frequency

Cleanings today are performed during scheduled dry docking and may be cleaned with in-water cleaning in between dry docks.

Vessel hulls are typically cleaned, and spot blasted when being Dry Docked. Depending on the established Hull Performance management procedures within a company the vessel is then cleaned several times underwater within the next years by divers. The fuel efficiency penalty for not cleaning in between dry-docking cycles can be a higher double-digit percentage figure. Both for financial savings and for achieving IMO fuel efficiency goals more frequent cleaning will be required in the future for vessels that are trading in areas prone to high fouling pressure. The ITCH project targets:

- Unrestricted trading availability of vessel
- Avoid logistics of third parties and harbour infrastructure
- Very low treatment cost
- No surface damage to sensitive antifouling paints

As the financial gain through fuel consumption reductions can be significant, cleaning frequency may increase if these goals are reached.

Most in water cleaning today is initiated when satisfactory fuel efficiency or contractual speed is no longer is obtainable. The methods used during such reactive cleaning abrades in the most cases the hull paint surface and is therefore increasing the viscous resistance. Lately researchers have argued for hull grooming with softer brushes to maintain the hull surface like new.

It is hard to measure the fuel efficiency effects of an ordinary underwater hull cleaning accurately. The results of the treatments can be shown in scatter plots where the variability often exceeds the gains of the cleaning. In common hull cleaning operations, fuel efficiency is measured before the vessel enters the unloading harbor. The vessel is cleaned and then departs. Weather, trim, draft and currents are normally different for before and after measurements. Beside this many shipping companies relies on noon reports.

7. Cost-benefit analysis

To determine the most economical frequency of cleaning the hulls a simple hull cleaning calculator was developed. The key assumption is according to, *Hunsucker et al. (2019)*, and anticipates no paint surface damage for soft brushing. An example shows yearly cleaning with In-Port cleaning compared to in-transit cleaning every 4 weeks. On average, the proposed case delivered a 7.7% decline in average consumption during a 5-year docking sequence. The purpose of the simulation is just to exemplify the process, not to make quantifiable statements about benefits in fuel efficiency.

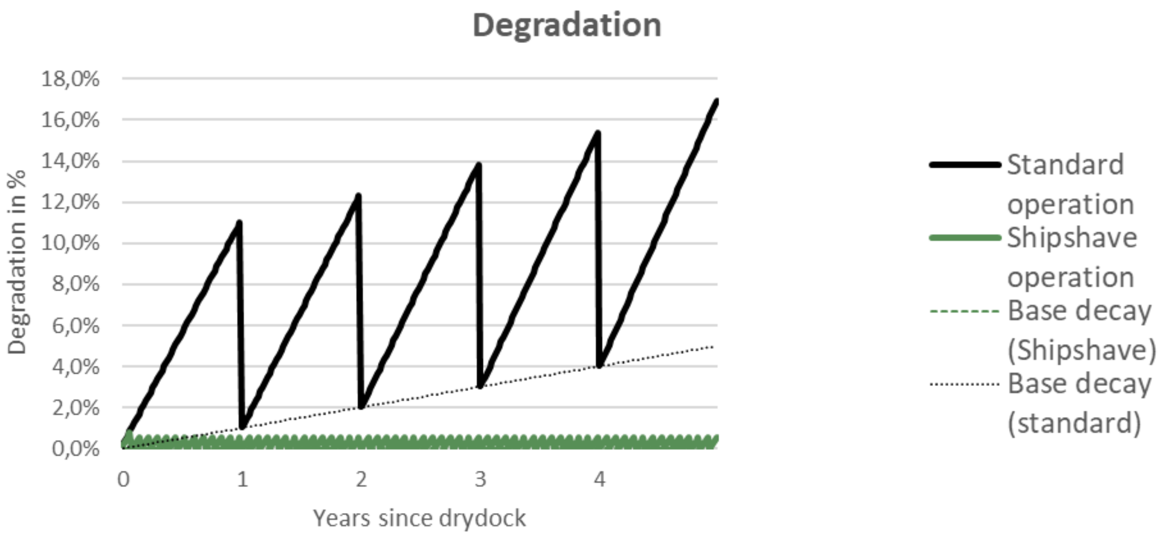


Fig.4: Hull degradation / cleaning time histories for different approaches

8. Hull cleaning cost

The variable cost components of ITCH hull cleanings are estimated to:

Cost element	
Idling of vessel and crew	No cost
Crew hours	Less than one shift
Disruption of trading schedule	No cost
Service crew and equipment rental	No cost
Scheduling and management	No Cost
Added fuel	Cost of drag during operation
Consumables	Less than 500 USD per clean

The hull cleaning tests that was performed with the ITCH system indicates that these assumptions are correct.

9. Testing

Testing has successfully been performed on numerous vessels with lengths from 60-200 m at speeds from 9-14.5 knots. The purpose with the testing has been to verify initial results, ensure that all product items work in concert and document cleaning results.

Fig.5: 3 years' fouling on an OSV

The tool was tested on a vessel at 9.2 knots. The hull had been in the water for 30 months without cleaning, predominantly in a shallow port more than 95% of the time. After the test, the boat was pulled up on a railed slipway and inspected. The findings were that almost all algae and soft fouling was removed by the brushing. Damages to the paint were not observed.

Another test was performed on an 8-year old Offshore Supply Ship of 5000 DWT, Fig.5. The ship had heavy algae fouling from 3 years of intermittent operation in temperate waters entirely covering the hull surface. The hull was shifting between black and green. The ITCH tool was used from bow to stern. The functionality was proven and the range of swipe velocity was confirmed. Where the ITCH had been operated repeatedly it fully cleaned the hull. A key learning was that developed fouling requires a larger number of swipes than simply grooming.

A method for removing calcareous fouling using the ITCH tool, but with a different removal mechanism was trialed on a ship on a slipway. The objective of removing barnacle cones without paint damage was achieved. The method works as projected, but piloting in the sea remains, because of lack of local vessels.

10. Further work

The method and tools are new, and the information presented is "hot off the press". The testing till date verifies tool functionality. It does not quantify benefits over full operation cycles so far. Further qualifications may be required for applications such as high or low speed, high seas, different antifouling systems and calcareous fouling.

References

HUNSUCKER, K.; RALSTON, E.; GARDNER, H.; SWAIN, G. (2019) *Specialized Grooming as a Mechanical Method to Prevent Marine Invasive Species Recruitment and Transport on Ship Hulls*, Impacts of Invasive Species on Coastal Environments, pp.247-265

Summary of Full-Scale Measurement about Propeller Performance of 14k Container Ship

Yasuhiko Inukai, Japan Marine United Corporation, Yokohama/Japan, inukai-yasuhiko@jmuc.co.jp
Norihide Igarashi, MTI, Tokyo/Japan, igarashi-norihide@jmuc.co.jp
Masahiko Mushiake, **Satoshi Kawanami**, Furuno Electric, Nishinomiya/Japan, {masahiko.mushiake,satoshi.kawanami} @furuno.co.jp

Abstract

We have put efforts to a full-scale measurement on 14k container ship in recent years. The results in the project were reported in the last two HullPICs. A special attention was paid to the flow field measurement using MLDS (Multi-Layered Doppler Sonar). The validity of MLDS has been well confirmed by a total of three onboard measurements. This paper mainly describes the accuracy of MLDS and shows a good perspective of full-scale Computational Fluid Dynamics calculation (CFD).

1. Introduction

A full-scale CFD has recently become available and is expected to enhance optimizations of hull forms, energy saving devices (ESDs) and propellers to reduce GHG emission. However, it has not been enough validated because of a lack of the number of full-scale measurements. To overcome this situation, a Japanese industrial project "i-Shipping", *MLIT (2016)*, and a worldwide joint research project "JoRes", *JoRes (2019)*, were launched and have been ongoing. Most notable in both projects is the flow field measurement using Particle Imaging Velocimetry (PIV), which is a well-established technique in model tests. The JoRes announced that they would open the measuring data and the relevant data including hull form and propeller. It means that benchmark data for a full-scale CFD will be provided for the first time. It is very good news for all the researchers and designers involved in this field.

Meanwhile, the authors have taken a different approach to the flow field measurement in recent years. We applied a Multi-Layered Doppler Sonar (MLDS) which is acoustic Doppler sonar capable of measuring relative water velocity at multiple arbitrary depths along ultra-sonic beams. MLDS is less expensive and much easier to install compared with other methods such as PIV. Thus, it has a great potential to increase the number of the validation data for full- scale CFD. To confirm the capability of MLDS for measuring flow field at stern, Nippon Yusen Kaisha (NYK), MTI Co, Ltd. (MTI), Furuno Electric Co. Ltd, (FURUNO) and Japan Marine United Corporation (JMU) started a joint research project on 14,000 TEU container ships in 2016.

We divided the project into two stages. On the 1st stage, one MLDS was installed to investigate if it has a potential to measure the flow velocity at the stern. After confirming its basic features, we proceeded to the 2nd stage and installed three MLDSs in the sister ship to expand the measuring area. The result on the 1st stage and the preliminary result on the 2nd stage were reported by *Inukai (2018)* and *Wakabayashi (2019)* respectively. To investigate the accuracy of MLDS more closely, further full-scale measurements were performed. Small modifications were made for MLDS each time by feeding back the previous results. Through totally three onboard measurements, the validity of MLDS has been well confirmed. This paper mainly describes the accuracy of MLDS and shows a good perspective of full-scale CFD as the design tool.

2. MLDS

MLDS was developed by FURUNO based on their commercial product model "DS-60" with revised signal processing algorism, https://www.furuno.com/files/Brochure/161/upload/ds-60.pdf. Flow velocities in the direction of ultrasonic beams emitted from a transducer (TD) can be measured using acoustic Doppler effects. The beam direction can be selected at every 30°, which enable us to measure the flow velocities in twelve directions per one transducer as shown in Fig.1. Six beams are at the ordinal position of TD and another six beams at the rotated position by 90°. We measured the velocity in the area shown in Fig.2 by applying three MDLSs in this project. The configuration of the measurement system is simple as shown in Fig.3. Holes of 125 mm diameter are required to be drilled on the hull for the equipping transducers. Then, the transducers are connected with electric wires to the transceiver units and recording PC which are put in appropriate places such as a steering gear room. Because "DS 60" has been a widely used as a speed log and is familiar to both shipyards and ship owners, it is easy to install and handle. The details were described by *Inukai (2019)*.

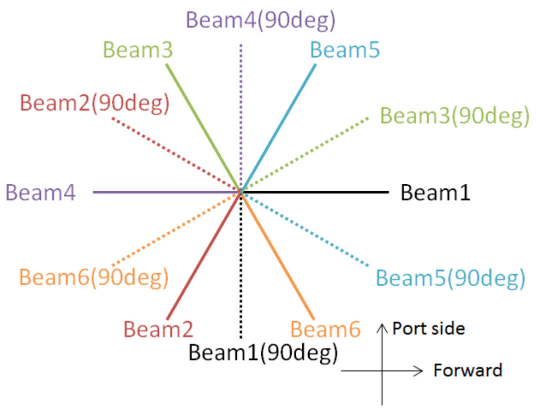


Fig.1: Directions of ultrasonic beams transmitted

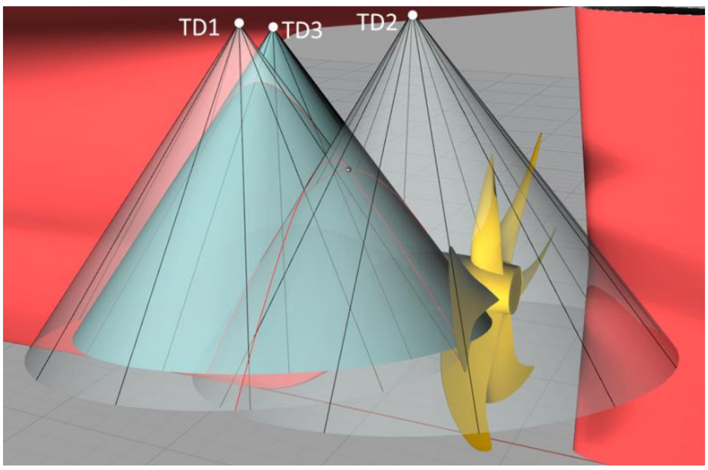


Fig.2: Measurement range with three MLDSs

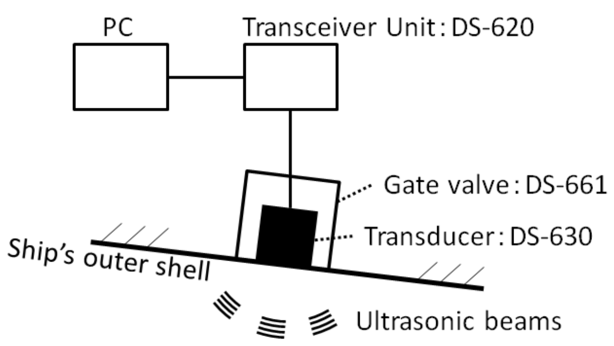


Fig.3: Configuration of system for MLDS equipped on 14,000 TEU container ships

3. Confirmation of accuracy of velocity measured by MLDS

The full-scale measurement was performed during the voyage from Antwerp to Suez in November 2019 on the same ship described in *Wakabayashi (2019).* We showed in the past that the flow velocities measured by MLDS and those simulated by CFD generally agree, but we have not mentioned how accurate the absolute values of the measurements are. To identify the accuracy of MLDS in the absolute sense, we compared the speed over ground (SOG) by MLDS with that by Global Positioning System (GPS), assuming the measured value with GPS is correct. Then, the measurement reproducibility and uncertainty were investigated. Through these investigations, it was concluded that MLDS can measure the flow field with very high accuracy.

3.1 Comparison of speed over ground using GPS

MLDS can measure not only a speed through water but also a SOG in the same way using acoustic Doppler effect. A SOG, V_G, can be derived with formulas (1) and (2) as a function of the beam transmitted angle, α, equipped angles of the transducer in the xz plane and yz plane, βxz and βyz, and the acoustic wave velocity in water, c. In addition, the seawater temperature should be taken into account because it influences both α and c. If the actual value of α, βxz or βyz, differs from the planned by 1 degree, it leads to the maximum 2% error in the SOG.

$$\overrightarrow{V_G} = |V_b| \cdot \vec{e} \tag{1}$$

$$|V_b| = \frac{c f_d}{2 f_0} \tag{2}$$

Where, V_G = speed over ground, V_b = velocity in beam direction, ***e*** is a transformation vector from the beam direction to the ship heading direction, which is a function of α, βxz and βyz, f_0 = frequency of transmitted ultrasonic beam, f_d = Doppler shift frequency.

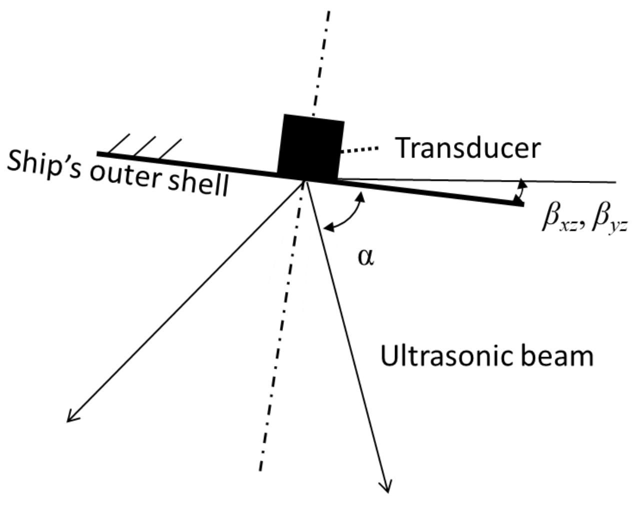


Fig.4: Measurement of speed over ground using MLDS

The SOG was measured in the shallow area between Antwerp and Southampton. Fig.5 shows the comparison of the SOG in the x and y directions measured by MLDS and GPS. The black lines indicate the values by GPS and marks by MLDSs. The different colours of marks correspond to the difference of the transducers. It can be seen that the SOG by all three MLDSs agree well with those by GPS. For each TD, the differences from GPS are only 0.1% to 0.3% of ship speed, *Vs*, in the measurement in the morning of 22nd November while the ship speed was stable. It indicates that the transducers were appropriately equipped, the angles of α were same as designed and the influence of sea water temperature on α and c were considered correctly. It was confirmed that MLDS can measure velocities very accurately in absolute sense.

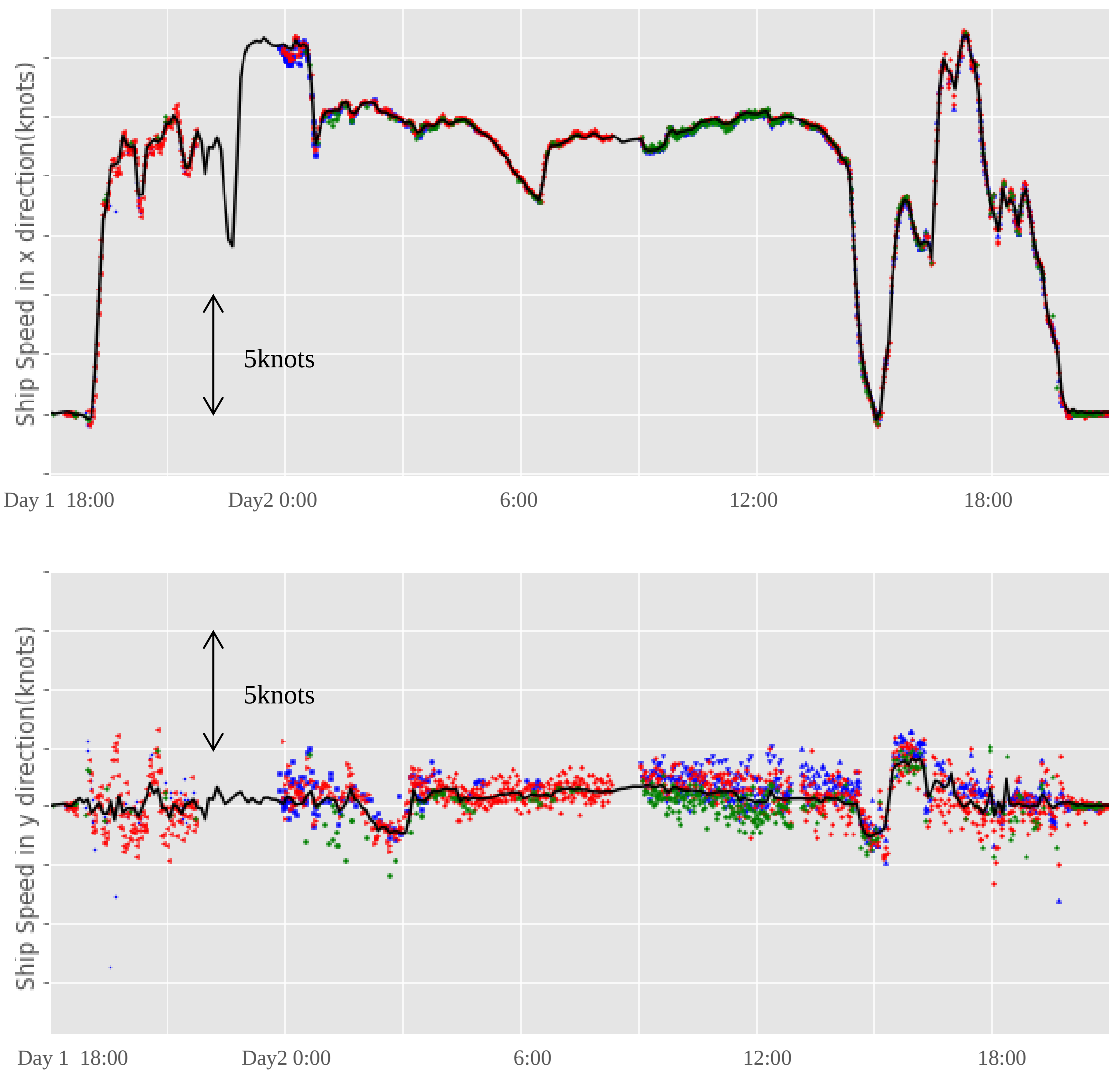


Fig.5: Comparison of SOG between MLDS and GPS (black lines: GPS, blue marks: TD1, red marks: TD2, green marks: TD3)

3.2 Reproducibility

We investigated the variability of velocities measured on different dates, including the previous measurement made seven months before by *Wakabayashi (2019)*. It is noted that the ship posture, i.e. draft and trim, location, voyage speed and sea condition are almost the same in the previous and this measurement. Fig.6 shows the velocities in beam directions, V_b, which consists of nine data sets plotted with different marks. The previous measurement is shown as marks of “x”. The horizontal axis indicates distance from the transducer to measuring point. To maintain the data quality, only data above the threshold of signal-noise (SN) ratio were extracted. The mean velocities in a measurement of which duration is about 10 minutes are normalized by V_s measured by a DS-60 equipped at the bow. The numbers and colours of the beam are as shown in Fig.1. It can be seen that the measured velocities are similar to each other regardless of the measurement date. To depict it more clearly, the standard deviation of a daily measured velocity against the averaged value on all dates are plotted in Fig.7. The standard deviations of the normalized V_b in most beam directions are within 1% V_s although those in the beam passing near the propeller or hull, ex. the orange marks in TD2-1, get large. From the above, a good reproducibility of MLDS was confirmed.

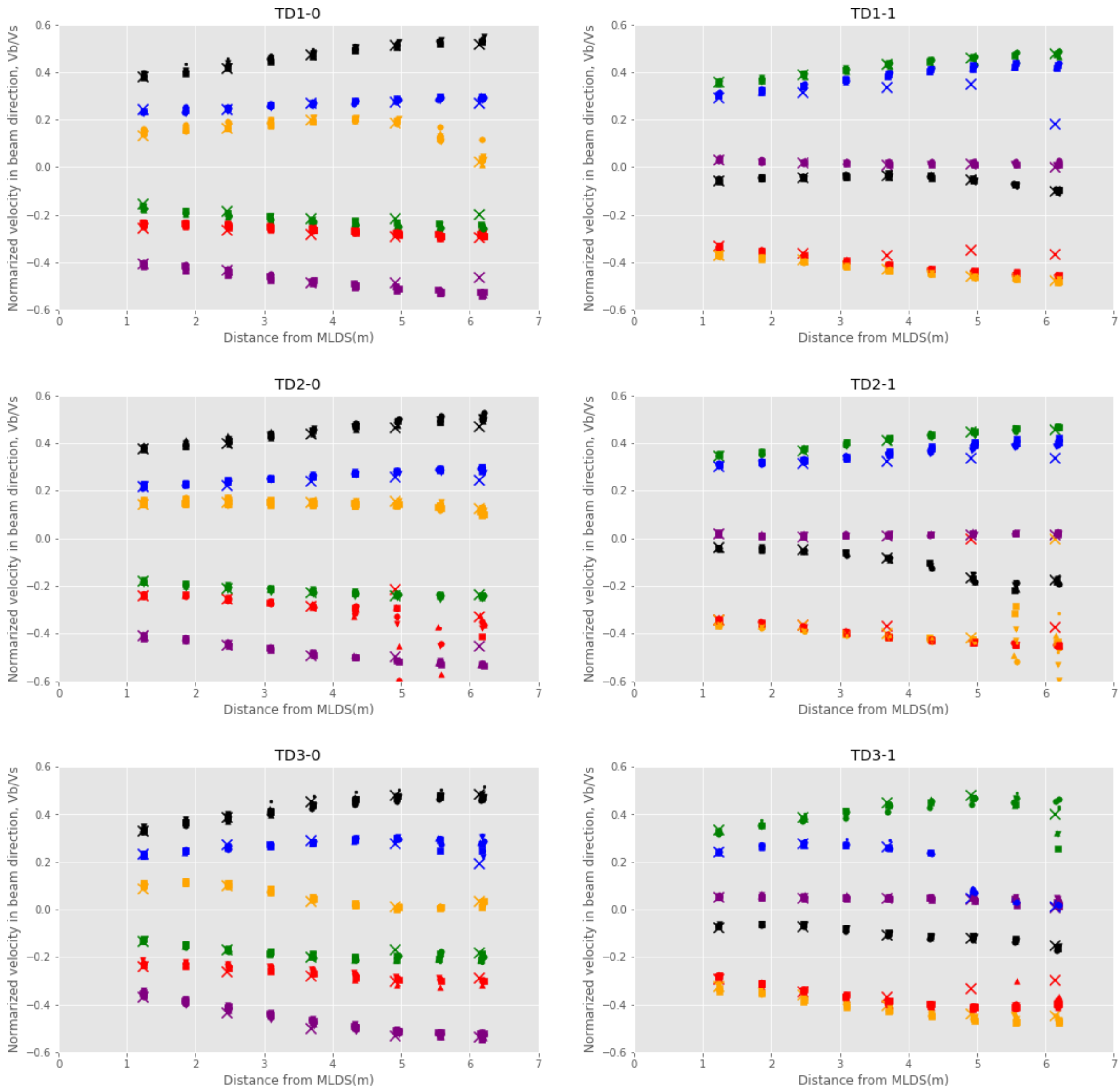


Fig.6: Normalized velocity in direction of each beam, V_b/V_s, measured on different dates; (black: beam1, red: beam2, green: beam3, purple: beam4, blue: beam5, orange: beam6); Left: the measured at the original position of MLDS, Right: the measured at the position after the rotation by 90°.

3.3 Standard deviation and uncertainty under a rough sea condition

The standard deviation of normalized V_b measured in calm sea is within 2% V_s as reported in *Inukai (2019)*. The ship encountered a very rough sea condition on Beaufort scale 8 during this measurement. To investigate how large the variation of normalized V_b would be under such a rough condition, V_b were measured continuously overnight. Fig.8 shows the time history of V_b/V_s and the data distribution for the beam1 of TD1 at the 3m far from the transducer. The standard deviations of V_b are around 4% *Vs*, which are larger than those in calm sea. However, according to type A evaluation in *JCGM (2008)*, the uncertainty of the measured data with a normal distribution is expressed by the standard deviation divided by square root of sampling number. As shown in Fig.8, the measurement by MLDS has a normal distribution in general. Accordingly, the uncertainty is almost zero because of large numbers of sampling data. If there is enough amount of sampling data, which is 10,000 in this case, the uncertainty of the measurement can be neglected regardless of the sea condition. It is expected that MLDS can advance the investigation on the influence of the sea conditions on the propulsive characteristics.

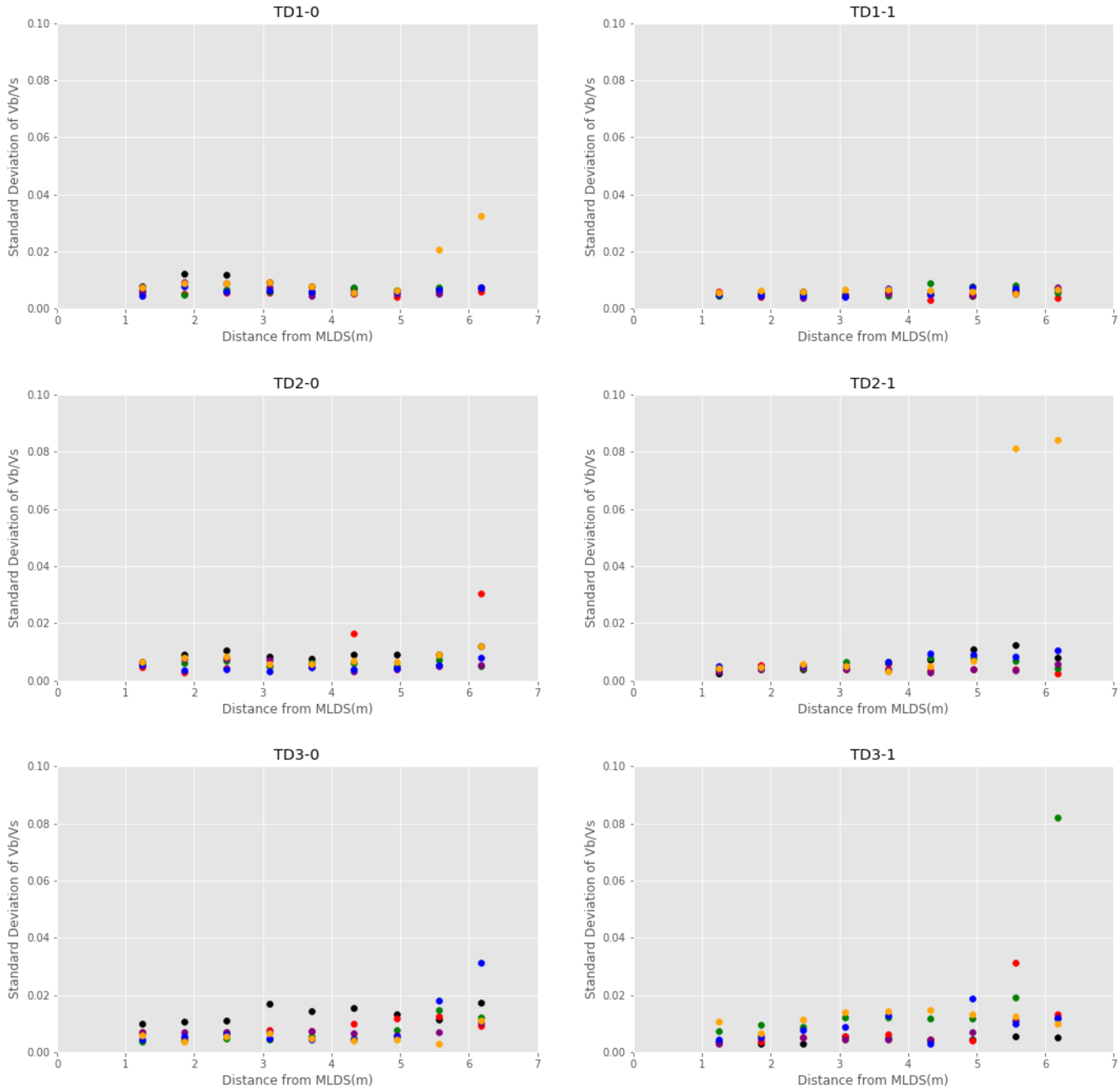


Fig.7: Standard deviation of normalized velocity in direction of each beam, V_b/V_s, measured on different dates (black: beam1, red: beam2, green: beam3, purple: beam4, blue: beam5, orange: beam6); Left: the measured at the original position of MLDS, Right: the measured at the position after the rotation by 90°.

4. Flow field simulated by full-scale CFD

Full-scale CFD was conducted by *Inukai (2018)* and *Wakabayashi (2019)* in the past. While *Inukai (2018)* used RANS Solver "SURF" developed by Japanese National Maritime Research Institute, *Hino (1997)*, a commercial software, FLUENT, was used in this study because more kinds of turbulence models can be chosen.

The validations of full-scale CFD were made in direct and indirect ways.

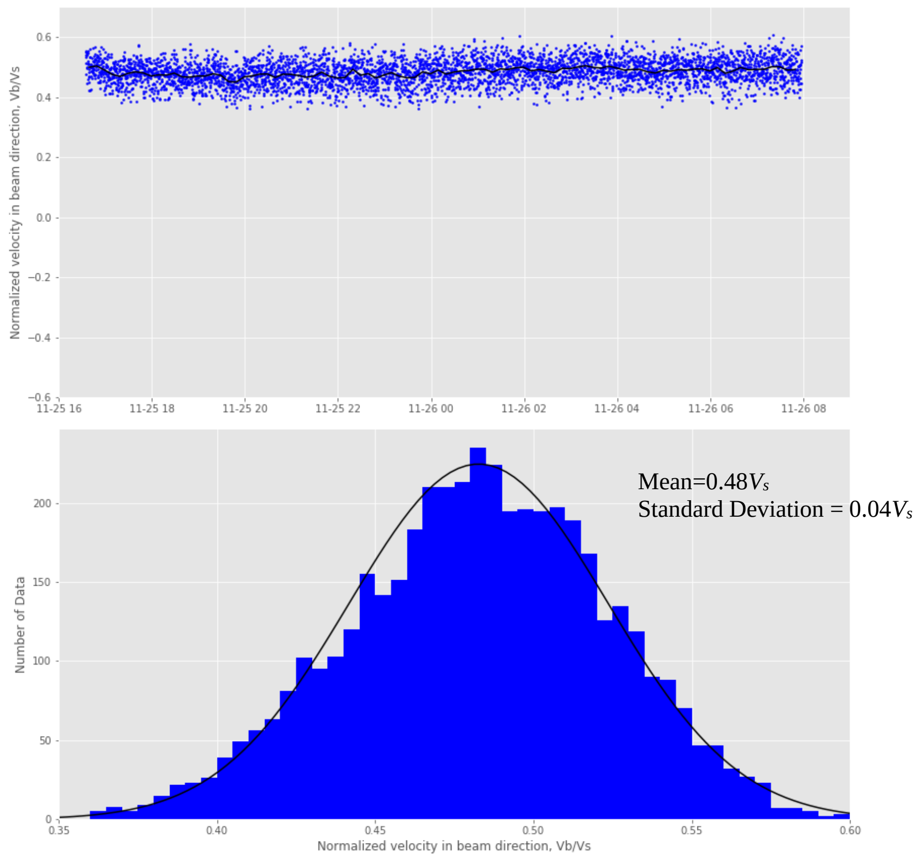


Fig.8: Velocity in direction of beams, V_b, measured during the voyage under a rough sea condition

4.1 Comparison on the flow velocity

Fig.9 shows the comparison of normalized velocities, V_b/V_s, between the measurement in November 2019 (marks) and the CFD (solid lines). As reported in the previous papers, the CFD generally agrees with the measurements. It can be said that the current CFD can simulate a flow field with reasonable accuracy. Through the study, we noticed that the simulated velocities vary depending on the physical models applied, ex. the turbulence model. We will proceed with further study on the appropriate computational setting to give the closest values to the measurement.

4.2 Comparison on the propeller cavitation and pressure fluctuation

It is well known that behavior of propeller cavitation is much influenced by the flow field where the propeller works. We conducted cavitation tests in the JMU cavitation tunnel of 2,600mm (L) ×600mm (H)× 600mm (W) by using two wake mesh screens reproducing different wake distributions to see which could show more similarity to the onboard measurements. One of the wake distributions is simulated by CFD and another is by the classical extrapolation method based on the wake measured in the model test by *Sasajima (1966)*, which is widely used in many tank facilities, *ITTC (2011)*. Fig.10 shows pictures of cavitation observed in the model tests and onboard. Except that the tip vortex got stronger at full scale, the cavitation pattern in the both wakes generally agreed with the onboard observation. However, the pressure fluctuations in the both wake meshes differ very much. Fig.11 shows the pressure fluctuation at the first blade frequency against the propeller speed. The onboard measurement agreed clearly with those in the CFD wake compared to in the Sasajima wake. This implies that the CFD gave better prediction for the flow field into the propeller. It is most important to impose an appropriate design condition when designing a propeller. In this case, the pressure fluctuation in the Sasajima wake is twice the value in the CFD wake and the onboard measurements, which gives excessive constraint on the design. The wise use of CFD is expected to help to optimize propeller designs by reducing design margins.

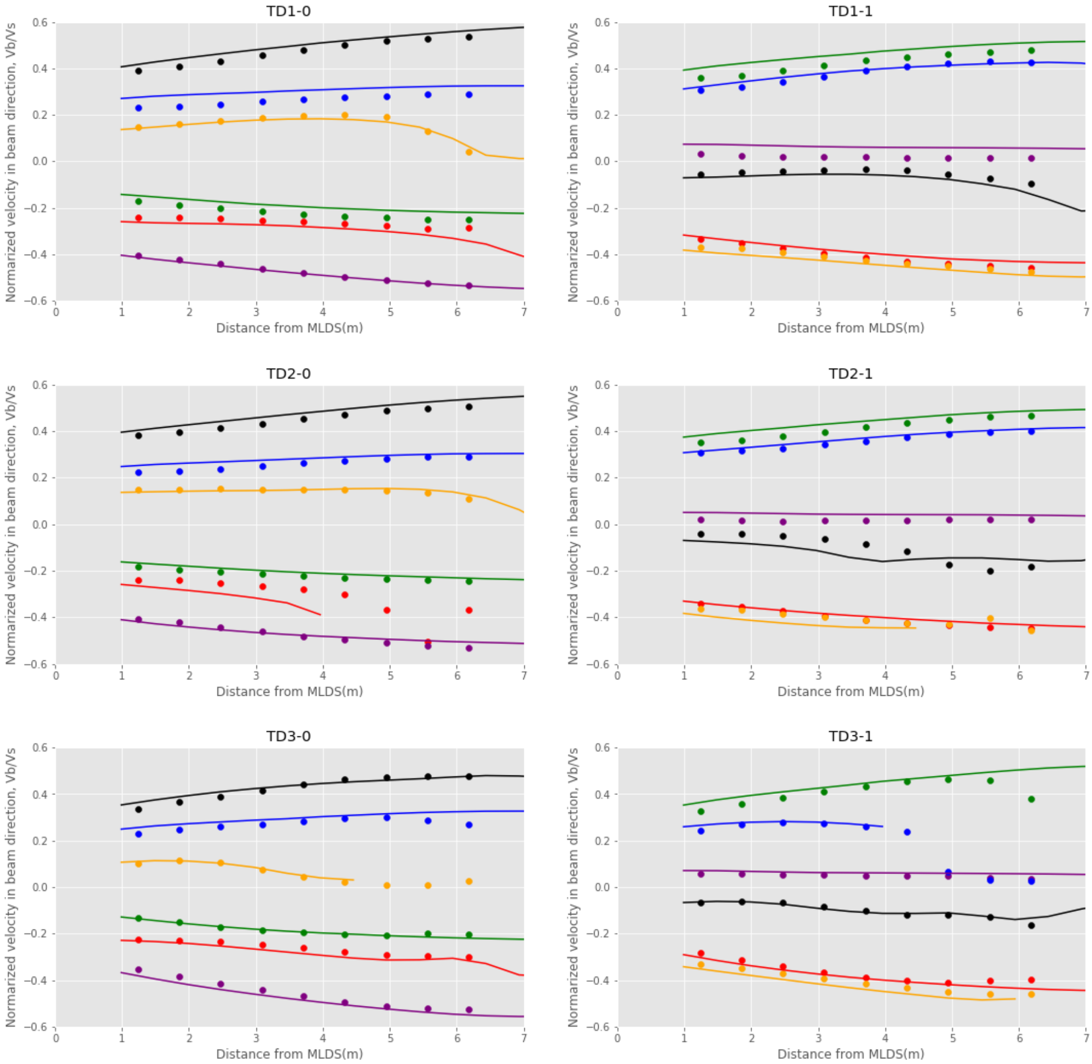


Fig.9: Comparison of normalized velocity in direction of each beam, V_b/V_s, between the measurements (marks) and CFD (lines); (black: beam1, red: beam2, green: beam3, purple: beam4, blue: beam5, orange: beam6); Left: the measured at the original position of MLDS, Right: the measured at the position after the rotation by 90°.

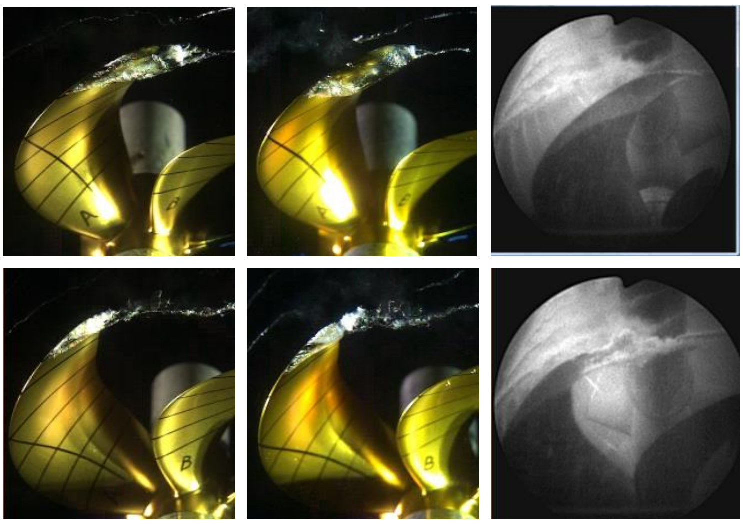


Fig.10: Comparison of cavitation pattern (left: model test in CFD wake, middle: model test in Sasajima wake, right: ship observation, upper: at the 35°, lower: blade at the 55°)

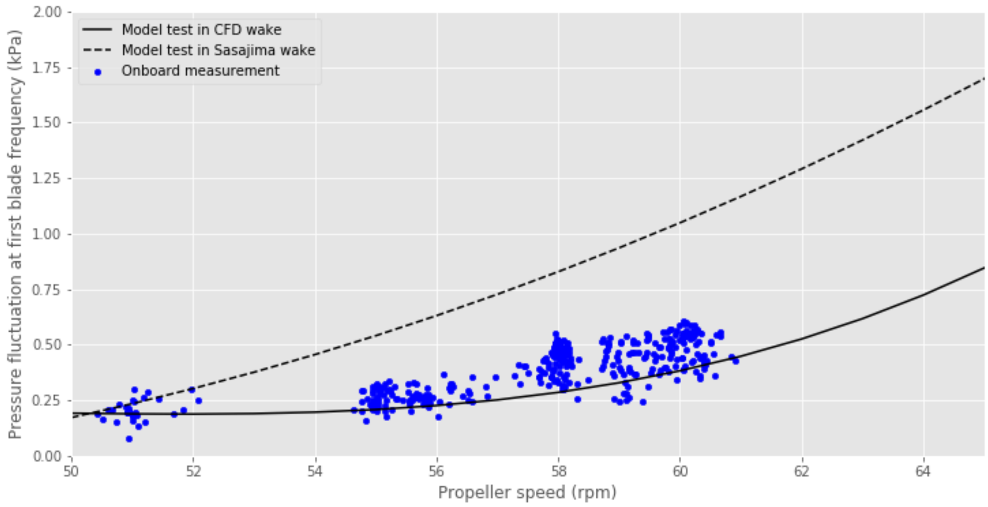


Fig.11: Comparison of pressure fluctuation at the first blade frequency (marks: onboard measurements, solid lines: model test in CFD wake, dotted lines: model test in Sasajima wake)

5. Summary and future works

Throughout the full-scale measurements on 14,000 container ships, we confirmed that MLDS has high accuracy in the measurement of flow field at stern. We expect that MLDS can overcome the situation where there is a lack of validation data for full-scale CFD thanks to its features easy to install and use onboard.

The study shows that the current CFD can simulate the flow field reasonably. We will proceed with further study on the appropriate computational setting to give the closest values to the measurement. A well-tuned CFD to accurately simulate flow field is expected to enhance full-scale optimization of ESDs or propeller. As easily imagined, a model-scale optimization is likely not to be optimum at full-scale as implied in *Inukai (2006)*. Most ESDs fitted in front of the propeller are designed to recover energy losses in the turbulent flow behind the ship. So, an accurate prediction of flow field where the ESD works is essential for the optimum design. As mentioned in section 4.2, the same can be said for a propeller design. The authors redesigned the propeller after the cavitation observation at the 1st stage. Consequently, the revised propeller with 1.2% higher efficiency had been applied to the following sister vessels, see *Inukai (2019)*. This is the example showing the importance of the design optimization fed back from the full-scale measurement. We will put effort to the full-scale optimization for ESD and propeller as a next step.

An ultimate goal is the optimization of hull shape by full-scale CFD. It is quite challenging at this moment because the accuracy in absolute sense is rigorously required against all the hydrodynamics characteristics such as frictional resistance, wave resistance, interactions between a hull and a propeller and so on. In this sense, thrust measurement is considered to play a big role for a next step, of which accuracy is now under investigation in the project on 14,000TEU container ship.

We plan to conduct another project on full scale measurement on VLCC this year. Same measuring items, i.e. flow velocity, pressure fluctuation, thrust and cavitation observation, will be included. Because the flow field behind a full ship like VLCC is more complicated than that behind a slender ship like a container ship, it is more interesting to see the capability of full-scale CFD. We are looking forward fruitful results similar to the container ship project.

References

INUKAI, Y.; SUDO, Y.; OSAKI, H. ; YANAGIDA, T. (2018), *Extensive Full-Scale Measurement on Propeller Performance of 14000TEU Container Ship*, 3rd HullPIC, Redworth

INUKAI, Y. (2019), *Full Scale Measurement of The Flow Field at The Stern by using Multi-Layered Doppler Sonar (MLDS)*, 6th Symp. Marine Propulsors, Rome

INUKAI, Y.; KANEKO, T.; NAGAYA, S.; OCHI, F. (2011), *Energy-Saving Principle of the IHIMU Semicircular Duct and Its Application to the Flow Field Around Full Scale Ships*, IHI Eng. Review 44/1

ITTC REPORT (2011), *The Specialist Committee on Scaling of Wake field*, 26th ITTC, pp.379-417

JCGM (2008), *Evaluation of measurement data – Guide to the expression of uncertainty in measurement'. JCGM 100:2008 GUM 1995 with minor corrections, Joint Committee for Guides in Metrology*, Bureau International des Poids Mesures, Sevres

JORES (2019), *Development of an Industry Recognised benchmark of Ship Energy Efficiency Solutions*, https://jores.net/

MLIT (2016), *i-Shipping(design)*, http://www.mlit.go.jp/maritime/maritime_tk5_000052.html

SASAJIMA, H.; TANAKA, I. (1966), *On the estimation of wakes of ship*, 11th ITTC

WAKABAYASHI, T.; INUKAI, Y.; YONEZAWA, T.; IGARASHI, N.; MUSHIAKE, M.; KAWANAMI, S. (2019), *Full-Scale Measurement of a Flow Field at Stern using Multi-Layered Doppler Sonar (MLDS)*, 4th HullPIC, Gubbio

Benefits and Realities of Ship Data Collection and Analysis

Trevor Harris, National Research Council of Canada, St. John's/Canada, trevor.harris@nrc.ca
Allison Kennedy, National Research Council of Canada, St. John's/Canada, Allison.Kennedy@nrc.ca

Abstract

Ship owners and operators are becoming ever more interested in data collection. However, the next step of analyzing the data is still in the early stages of being realized. The National Research Council of Canada has been performing vessel monitoring with Canada Steamship Lines with the goal to determine operational baselines and monitor fuel efficiency. The intricacies of these multi-variable systems prove that perfect fit lines and clean interpretable data is more challenging than it seems at first conception. Comparisons of like transits has yielded a standard of repeatability to both baseline what would be expected, and track improvements to operations over time. In addition, continual engine performance fuel additive trials were also conducted. Data collection of this sort gives operators direct information on how fuel, and thus costs, can be lowered validating the necessity and advantages to data collection in the first place.

1. Introduction

This paper describes a subset of the work that was conducted by The National Research Council of Canada (NRC) on the Canada Steamship Lines (CSL) vessel, the 'CSL Thunder Bay'. Operational data from October 2017 to January 2020 was collected and analyzed by the NRC culminating in performance characteristics and operational metrics. The purpose of this effort was to baseline the typical operational performance of the vessel, and to detect when deviations from this performance occurred on a daily basis.

The 'CSL Thunder Bay', Table I, is a trillium class self-unloading bulk carrier built in 2013. It primarily operates within the Great Lakes and St. Lawrence River area. The vessel has one main engine, a single shaft, a power take-off unit and three auxiliary engines.

Table I: CSL Thunder Bay General Particulars

Parameter	Value
Length Overall (m)	225.50 m
Breadth Moulded (m)	23.76 m
Deadweight	34,490 tdw
Gross Tonnage	24,430 GRT
Number of Main Engines	1
Number of Auxiliary Engines	3

Data was transferred from CSL to NRC on a daily basis. Each file contained data that was acquired during the previous 24 hours. These files were typical CSV files containing time stamps and values for 343 channels. The data was loaded into a Matlab® software environment upon which all analysis occurred.

NRC has developed an object-oriented codebase specifically for analyzing ship data. This multi-layered codebase had provisions for handling units, time varying data, database provisions, and a host of data processing tools used within this project and others.

As is the case with modern vessels and the ever-increasing technology, the data acquired on the ship was very clean and required little pre-processing. Historically, NRC has had issue with fuel sensors, particularly vein-type sensors which tended to produce discretized data if the fuel rates are low, *Kennedy (2018)*. The data loaded each day was parsed and combined with all historical data loaded to that date, adding to the ever-increasing database of time series data.

2. Segmentation and Statistics

Next the data was split into segments based on geofencing zones supplied by CSL. The limits for each zone is defined based on discrete operational areas, such as lock transits, lake crossings, and constricted waterways. The direction of the transits through each segment were determined as either upbound (generally east to west) or downbound (west to east). Fig.1 shows an example of the vessel transit during October of 2019, transiting through 5 zones within the northern section of the St. Lawrence River.

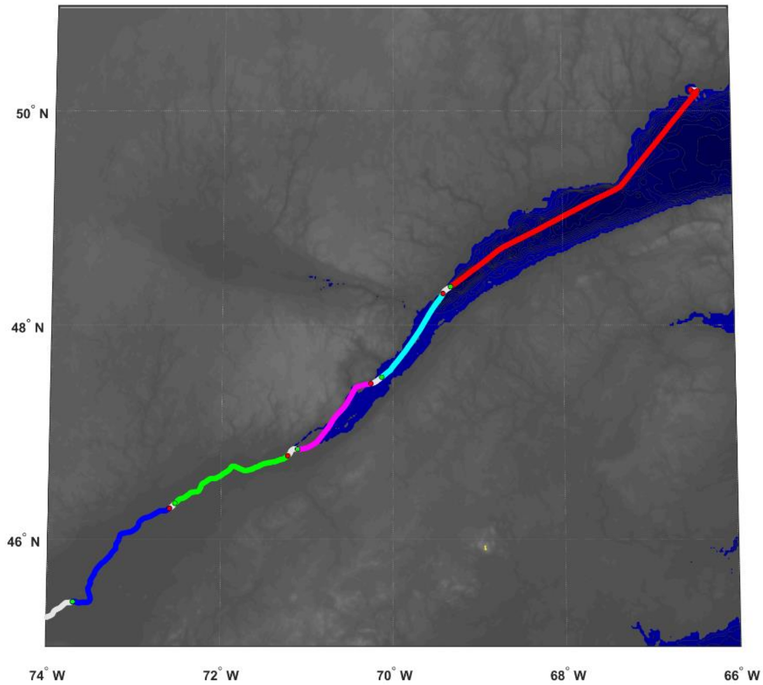


Fig.1: Geofenced Zones

Statistics for each segment were then calculated, such as the distance the vessel travelled in each specific zone, the fuel consumed during the transit, the fuel consumed over distance, and the total transit time. Beyond this, the mean, stand deviation, maximum value, and minimum value for each channel was also calculated. All these values were stored in a separate, but related statistic database complimentary to the time series database.

3. Performance Curve Generation

3.1. Introduction

The next step in the analysis was to generate a set of performance curves containing data from that day overlaid with the entire historical data set. The main purpose of these plots was to determine data anomalies and report to the ship operators on a quick turnaround to remedy the situation. Four primary curves discussed in this paper are listed in Table II.

Table II: Performance Curves

Performance Curve #	X Axis	Y Axis
Curve 1	Speed Through Water	Shaft Power
Curve 2	Fuel Consumption Rate	Shaft Power
Curve 3	Shaft Power	Main Engine SFOC
Curve 4	Auxiliary Engine Power	Auxiliary Engine SFOC

Upon initial design of this concept, it was presumed that outliers would be easily spotted through regular inspection or simple statistical deviations. However, data from ships is much more spurious than one would initially imagine. Consider, for example, the Shaft Power vs Speed Through Water curve in Fig.**2**.

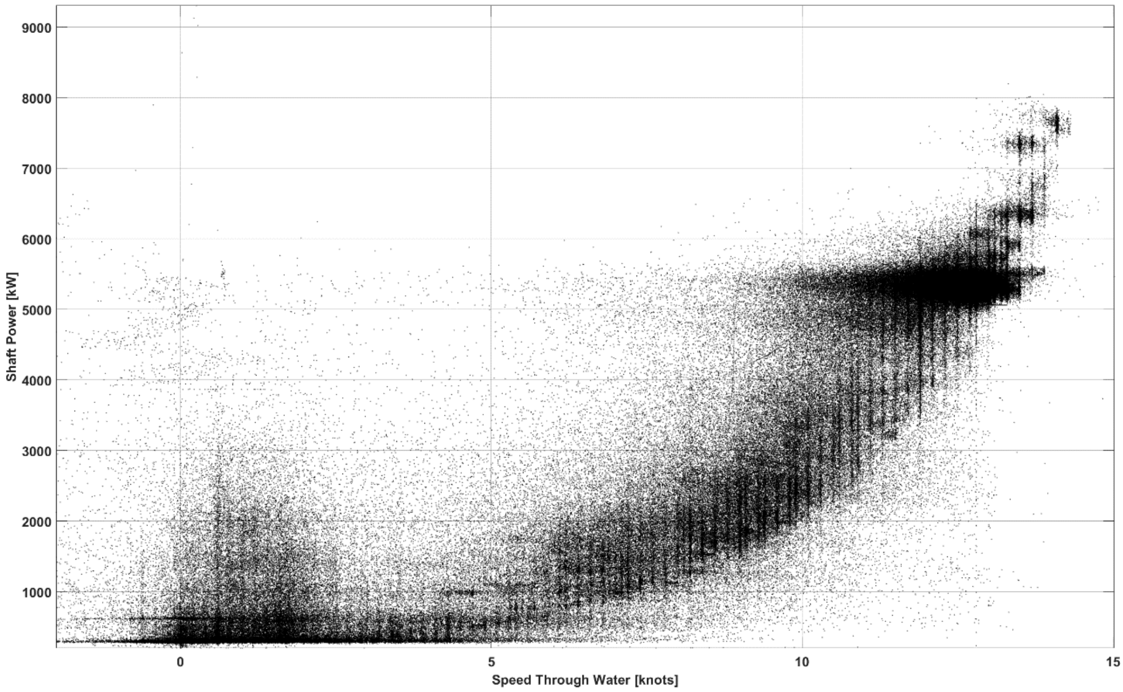


Fig.2: Shaft Power vs Speed Through Water

While the data does somewhat follow a third order curve, there is significant asymmetric spread at various portions of the curve. Namely, in the 0 - 2.5 knot range (where docking and maneuvering occurs) and at shaft powers between 5,000 and 5,700 kW (cruising power range). Further to this, 60% of all the data plotted here actually resides within this 5,000 - 5,700 kW range. Due to these difficulties, an automated statistical method was developed to detect outliers.

The irregularity of ship data results from both operational and environmental factors. From an operational point of view, consider the 5,000 - 5,700 kW cluster of points. The machinery on a vessel such as this is optimized to run at a specified power output to maximize efficiency. As such, the operators of the vessel typically set a cruising “power” rather than a cruising “speed” when in unrestricted waters. The variance of weather, current, and vessel loading tends to spread the data out between 10 - 14 knots. Likewise, during maneuvering in the 0 - 2.5 knot range, the vessel experiences variations in power between 0 - 3000 kW. This is caused by short bursts of power (kicks) and drifting.

As such, a method beyond a simple polynomial fit was necessary to define the performance curves. A statistical approach was developed in consultation with CSL to define the performance curves and detect anomalies.

3.2. Anomaly Detection Methodology

It was determined to use a percentile bin method to determine outlying anomalies. First, the data in a particular performance curve was separated in 25 bins (the number of bins were determined through test-cases). The bin size is determined such that each bin contained an equal number of datapoints. Consider Fig.3, showing the bin limits calculated for the data in the example above. Note that the labels for bins 15 to 24 are omitted due to space requirements.

Next, for each bin, it was calculated where 60% and 70% of the data lies above and below the median of that specific bin. Four limit curves were thus generated, with the X-values being simply the centre of each bin, as can be seen overlaid in Fig.4.

The final step in the process is to plot the data from the daily data and compare it to the historic performance curves. An anomaly was flagged if 5 minutes of consecutive data lay above or below the 70% lines. To finalize this example, consider Fig.5 which shows a single anomaly (red markers) that occurred during a day in October, 2019. This anomaly appears to result from a high acceleration of the vessel where the power was brought up quickly and the vessel took several minutes to reach cruising speed.

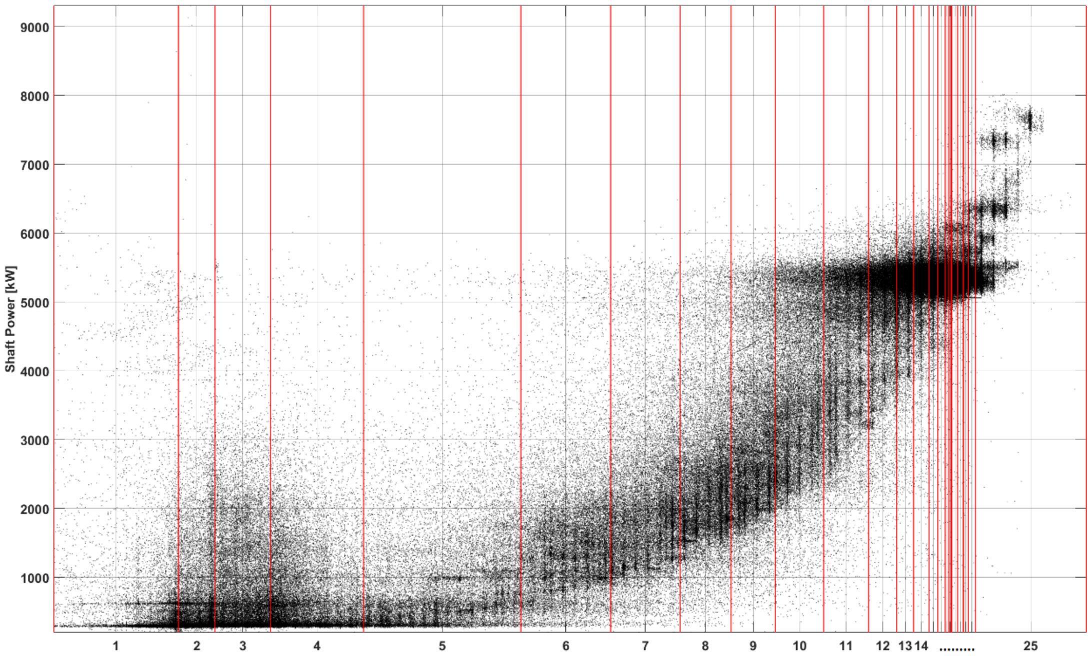


Fig.3: Bin Sizes

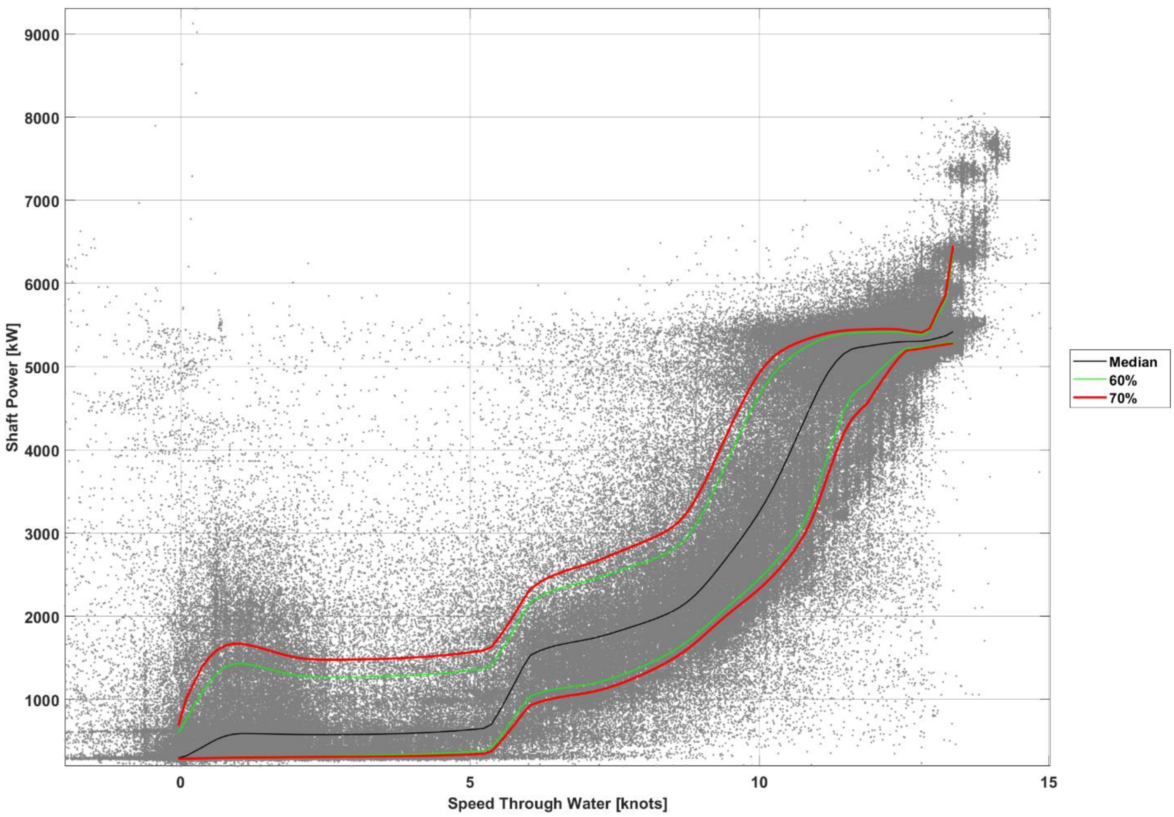


Fig.4: Performance Curve with Percentiles

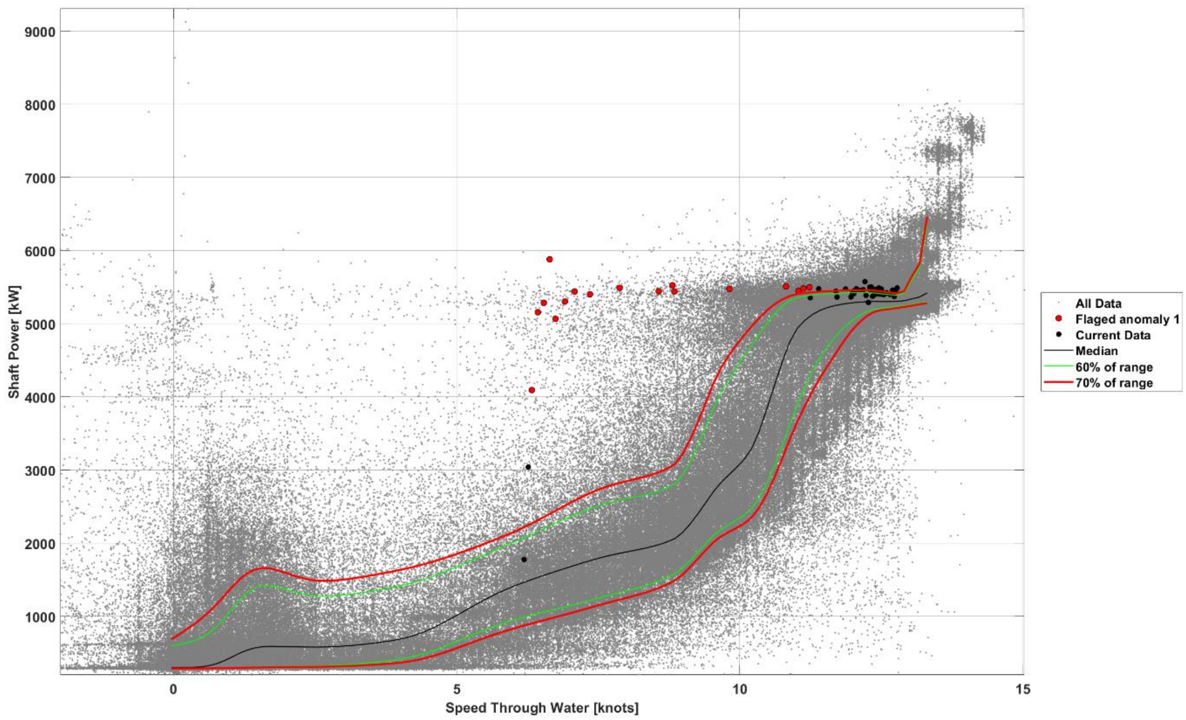


Fig.5: Curve 1 - Anomaly Detection

4. Performance Curves

Fig.6 to 8 show the remaining performance curves listed in Table II and the daily anomaly detection for a single day in October 2019. During this day, there was only one anomaly detected and it related to the ME SFOC versus Shaft Power. This is shown in Fig.8, where the ME SFOC was actually lower than typical for that operating power. A summary of these plots and a table of all anomalies, including some general information such as location and duration, were populated and sent to CSL on a daily basis throughout the reporting period.

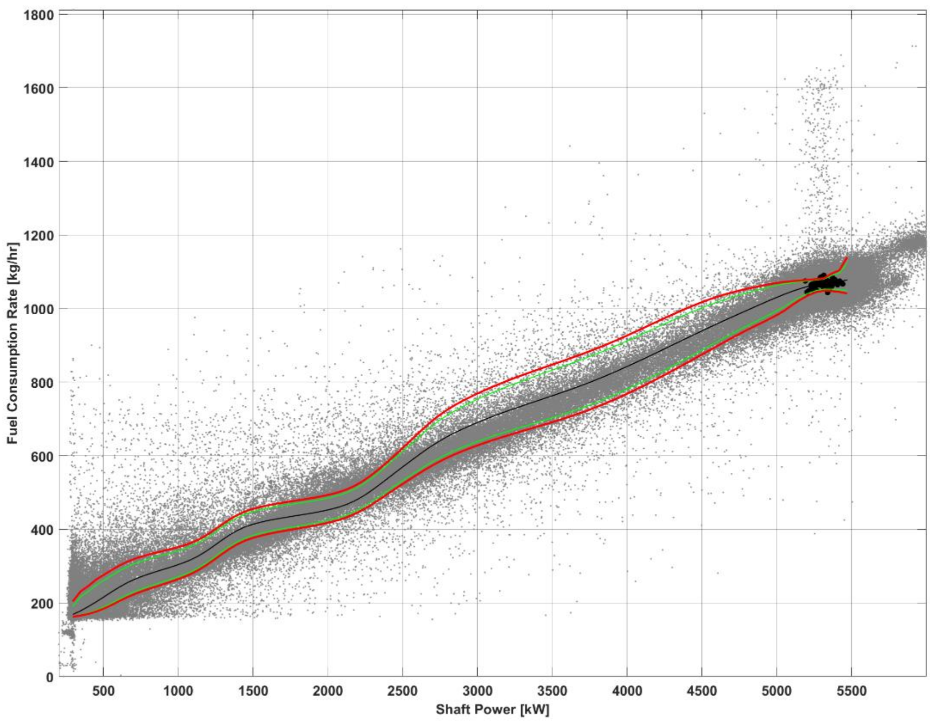


Fig.6: Curve 2 - Anomaly Detection

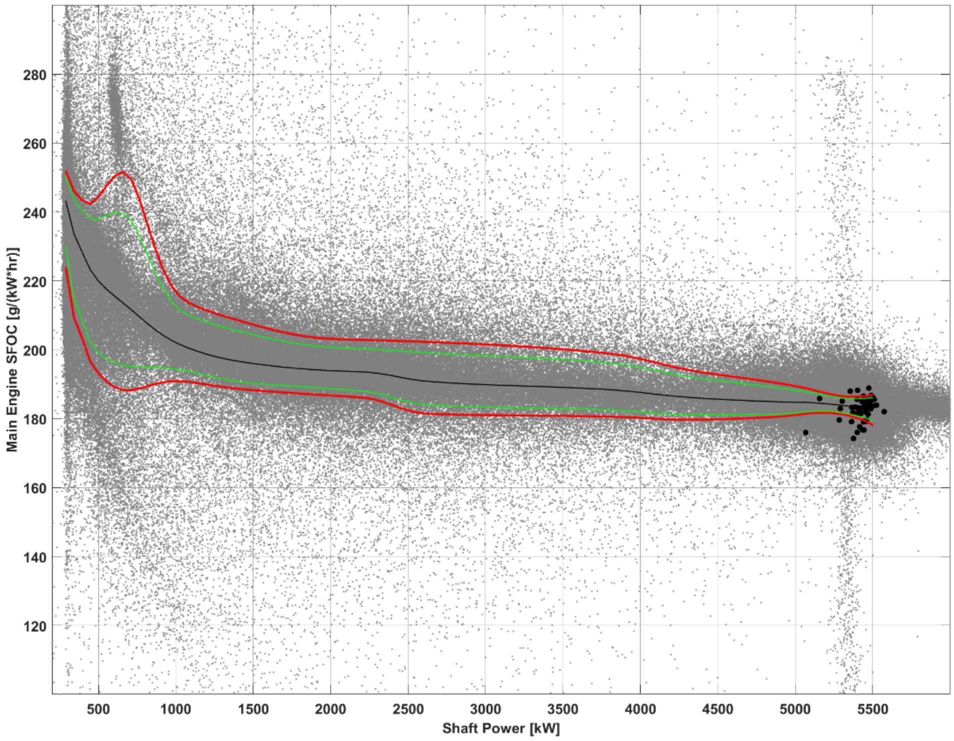


Fig.7: Curve 3 - Anomaly Detection

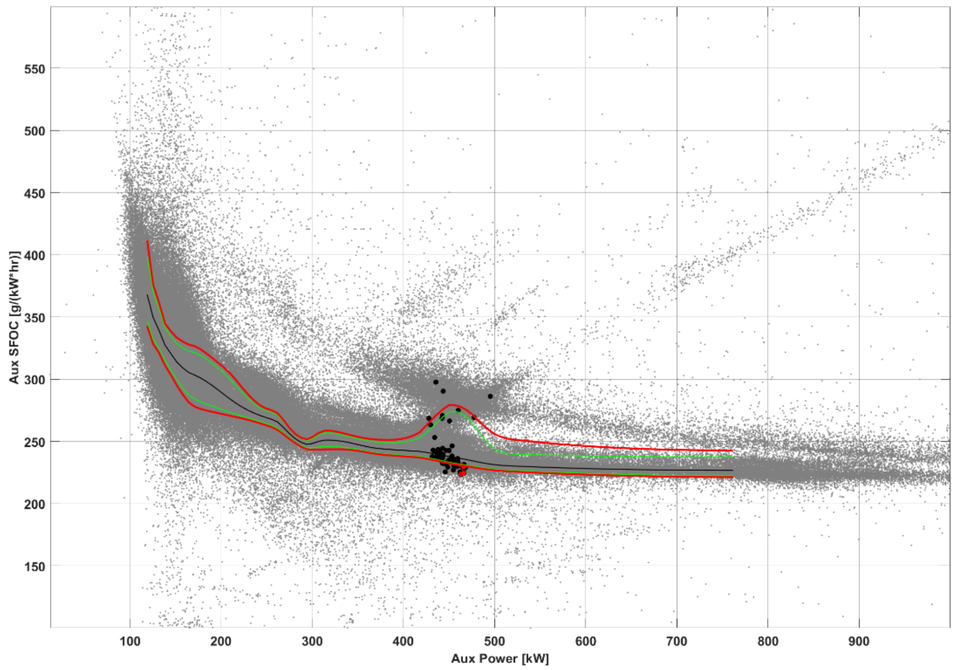


Fig.8: Curve 4 - Anomaly Detection

5. Performance Curves By Year

Each performance curve was also plotted to show potential differences in three operational years. As an example, Fig.9 shows performance curve 1 with each year represented as a different marker color. An interesting difference between the different operating years is that the highest portion of the performance curve, namely above 7000 kW, contains no data from the 2019 season.

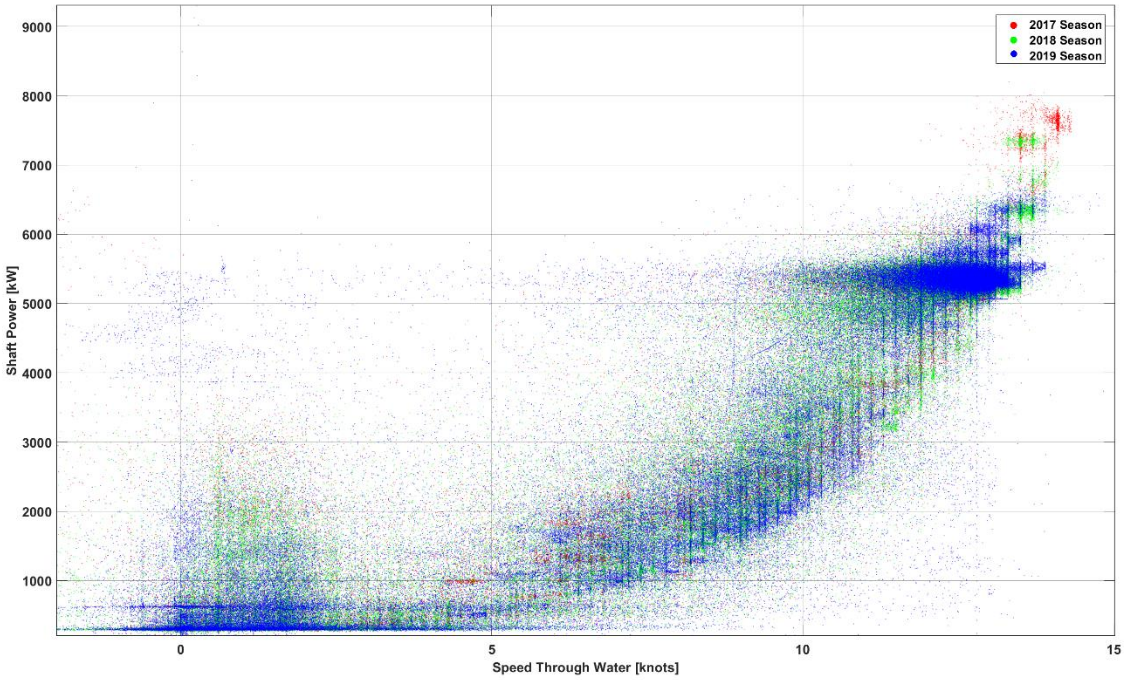


Fig.9: Curve 1 by Year

Through index parsing, it was determined that the high-power instances from 2017 and 2018 occurred as 4 separate data clusters. Plotting these instances on a map, it can be seen that they all occurred in generally open water while transiting various lakes. Inspection of apparent wind speed at this time did not yield any particularly high values, and as such it is unlikely that these events resulted from harsh weather.

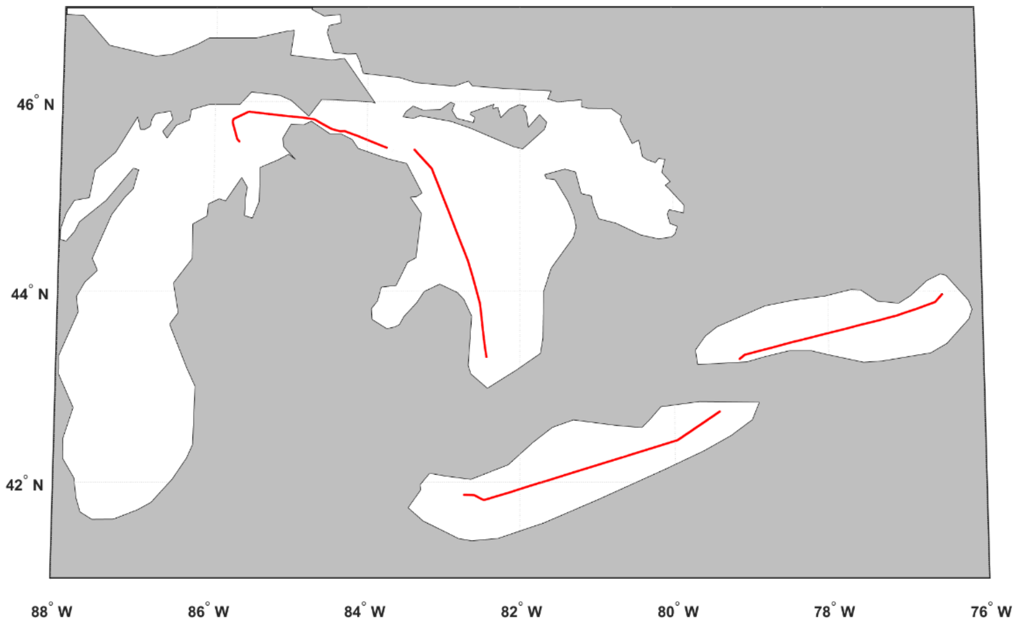


Fig.10: High Power Locations

6. Zone Statics

Since the vessel operates in a prescribed area, multiple passes through the zones as defined in section (2 were also analyzed for consistency. Specific metrics were tracked over time and compared between transits through the same zone. To exemplify this, consider the two graphs in Figs.Fig.**11** and Fig.**12**.

The Lake Erie transits show high consistency with both mean vessel speed and fuel consumed over distance. The Lake Superior transits show a slight deviation from the norm late in the 2017 season (the very first data point). While vessel speed was lower than average, the fuel consumed over distance value was actually higher.

The vessel draft during this transit was consistent with all other transits. The wind speed during this transit was higher than typical, as can be seen in Fig.13, outlining the wind speed as red dots overlaid against the wind speed for 3 weeks around this period. Thus, the likely culprit of this anomaly was environmental.

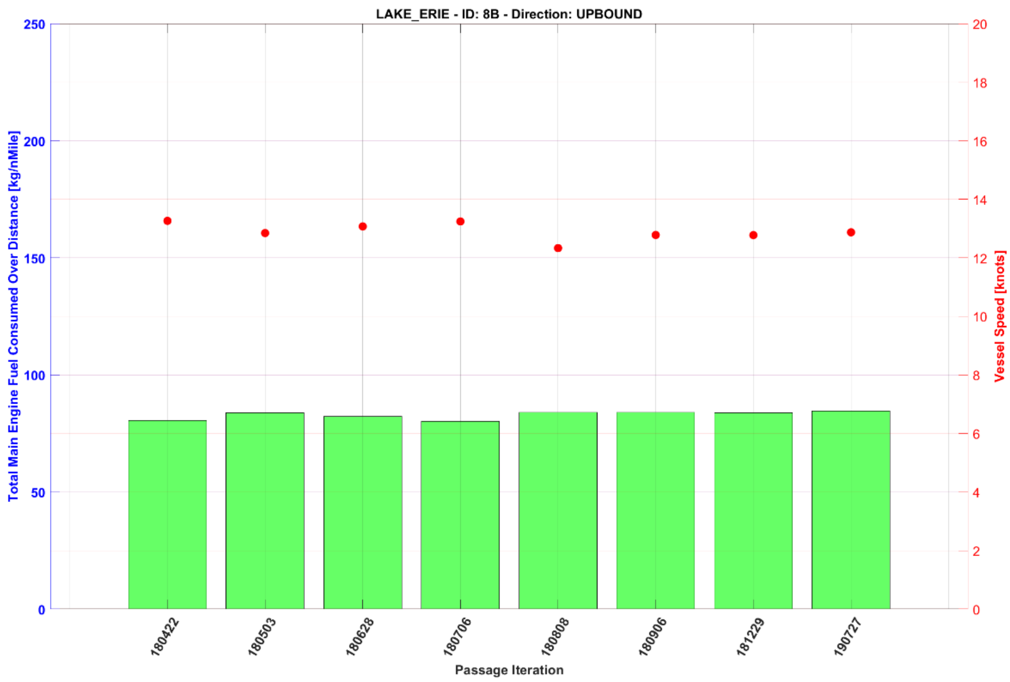


Fig.11: Lake Erie Transit Comparison

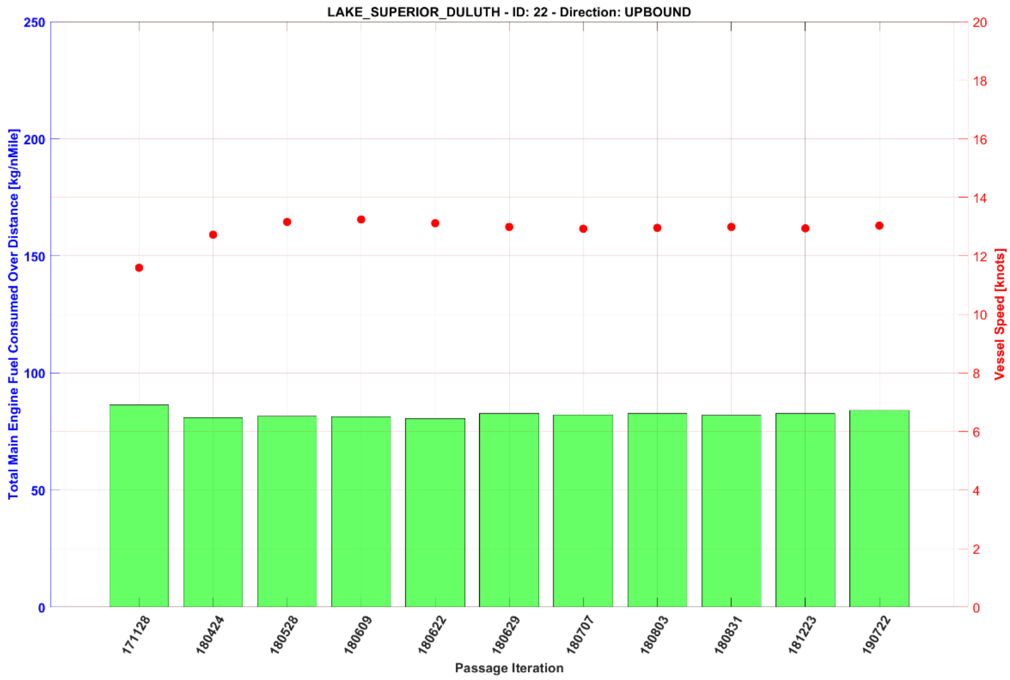


Fig.12: Lake Superior Transit Comparison

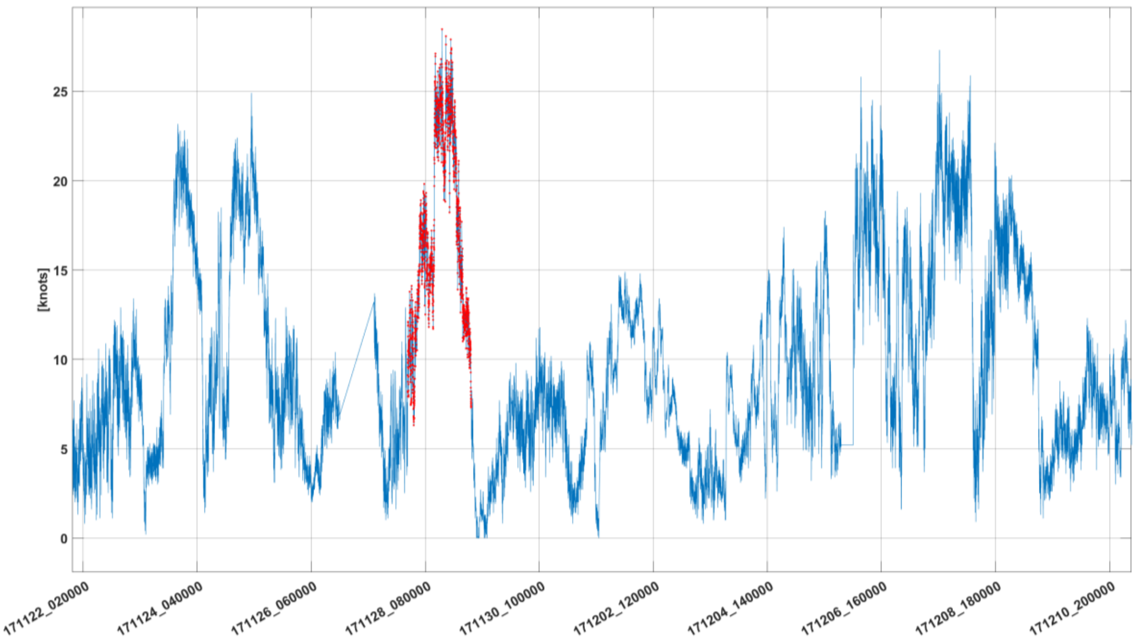


Fig.13: Wind Speed During Lake Superior Transit

7. Fuel Additive Trial

A fuel additive trial was completed on the 'CSL Thunder Bay' between October 1st and December 13th of 2019 in an attempt to improve vessel fuel efficiency. To validate its effect, the Specific Fuel Oil Consumption (SFOC) of the main engine was evaluated prior to and subsequent to the trial event. The average SFOC per week was calculated along with the standard deviation of SFOC during each week. This was plotted for all data between April 2019 and January 2020 to assess any trending, Fig.14. The standard derivation is plotted as bars against the mean, shown as dots. In general, the SFOC ranges from 175 to 275 g/kW*hr for the time period investigated. The SFOC for the two-week trial period falls within the data spread for the entire time period considered. As a result, it is difficult to distinguish any difference in SFOC performance resulting from the fuel additive trial from this plot.

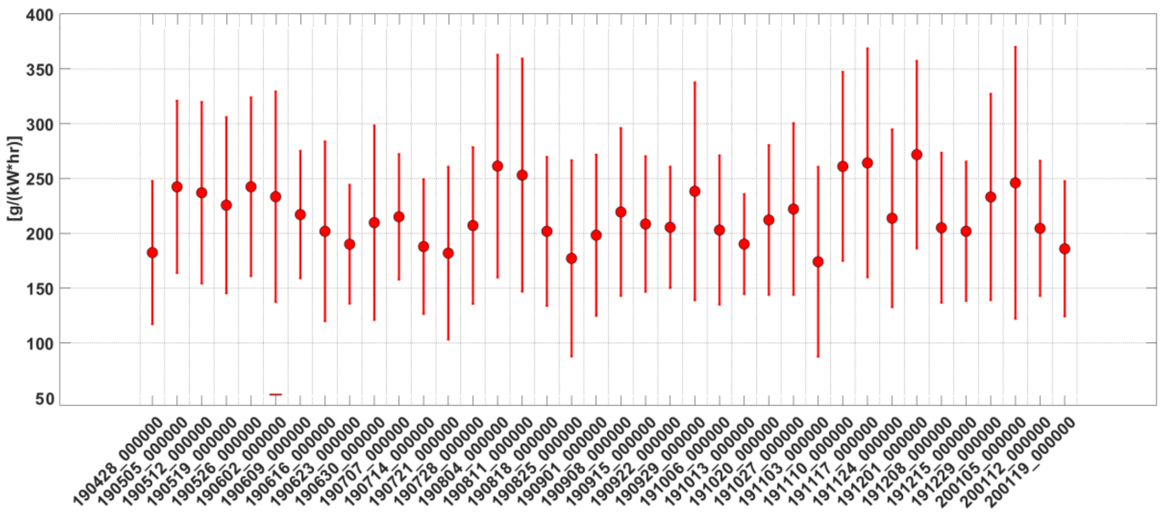


Fig.14: SFOC Over Time

To investigate further, a daily average SFOC was assessed as seen in Fig.15. A period directly after the fuel additive trial during which the daily average SFOC is slightly lower than the average value for the remainder of the period can be observed, as indicated. This lower SFOC occurred between October 12 and November 1, 2019.

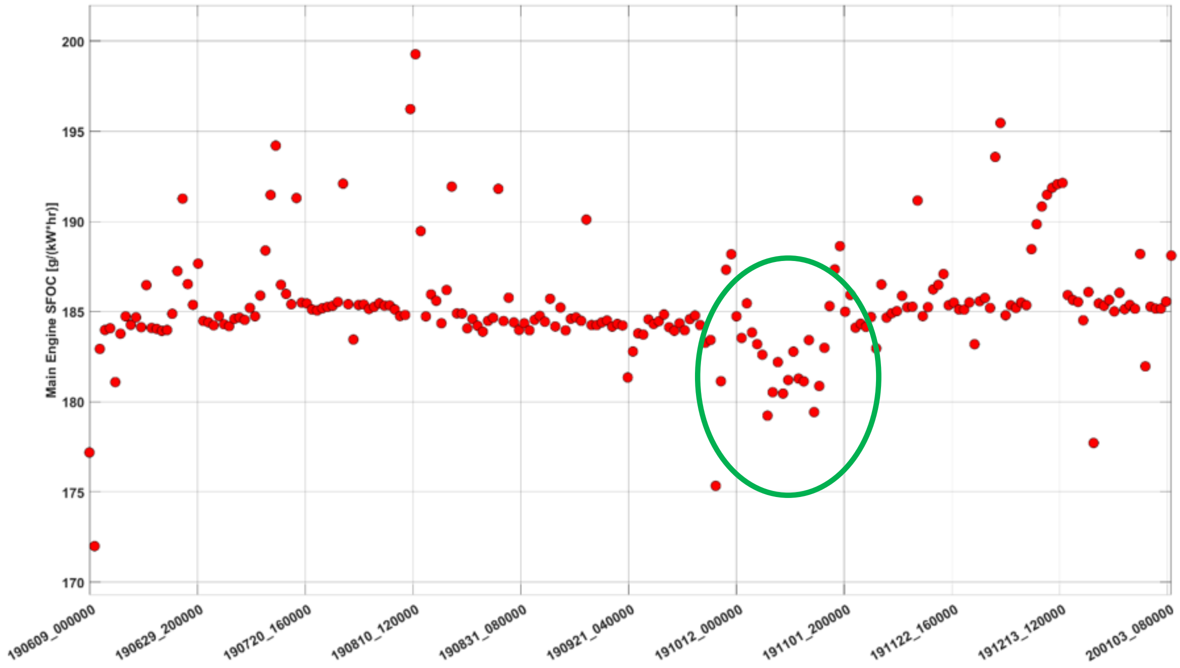


Fig.15: SFOC Over Time - Daily

8. Conclusions

The analysis of operational vessel data is challenging and complex. There are many factors, external, operational and vessel condition related, that influence the data. Specialized filtering and sorting techniques are required to ensure the data is representative and does not contain error. The preparation of this type of data set can be time consuming but is necessary for accurate analysis. However, the benefits of the analysis of operational vessel data are significant. Insight from this type of analysis can lead to increased operational efficiency, decreases in fuel consumption and the development of information driven operational procedures. This can result in savings for vessel operators and result in an overall greener fleet.

Future work beyond that described in this paper, could include the analysis and comparison of data from other vessels of the same class as the 'CSL Thunder Bay'. This would allow for a comparative analysis of engine performance, fuel consumption rates, auxiliary power, and crew variations between the entire class of vessels.

References

KENNEDY, A.; HARRIS, T. (2018*), CSL Niagara Phase II Analysis*, National Research Council of Canada.

A Study on Improving Reliability of Performance Indicators

Najmeh Montazeri, Vessel Performance Solutions, Lyngby/Denmark, nmo@vpsolutions.dk
Søren Vinther Hansen, Vessel Performance Solutions, Lyngby/Denmark, svh@vpsolutions.dk
Jakob Buus Petersen, Vessel Performance Solutions, Lyngby/Denmark, jbp@vpsolutions.dk

Abstract

In this paper, results from some ship performance analyses are shown. The analyses are based on a autolog stable-period algorithm that is applied on different data sets from several merchant ships. Ways to improve the reliability of performance indicators are considered. The speed through water is used for calculation of added resistance and the scatter is compared to added resistance based on speed over ground. In addition, speed through water obtained from wave radar measurements and hindcast current measurements is compared to traditional speed log measurements. Furthermore, uncertainty levels of added resistance based on different methods and different weather sources are compared. The uncertainty evaluation is based on the least-square fit, the slope and the confidence interval in the added resistance trend.

1. Introduction

The content of this paper follows *Montazeri et al. (2019)*, where a methodology for using autolog data for performance analysis is introduced. In this paper, two bulk carriers are considered as case studies. The sensor measurements are received from the vessels with 30 seconds interval as instantaneous measurements. The filtration (stable period detection) and averaging procedure in VESPER is applied as described in *Montazeri et al (2019)*. The time series are filtered and averaged to lighten and smoothen the analysis. The processed data are transferred to the Vessel Performance Analysis engine (VPAe) of VPS and the added resistance due to fouling is calculated over time using different data sources. The influences of changing the source of the speed signal and the source of the weather are investigated.

In the process of calculating added resistance, we deal with different uncertainties, which comes from measurement errors, human errors, modelling issues, etc. In order to have a good understanding of the accuracy of the predicted performance indicator, we need to quantify the estimation reliability. In VESPER, we have been using the trend reliability score for this purpose, which is used in the next sections. As a further refinement, the confidence interval is another algorithm that is being developed for a more precise and more consistent evaluation of trend reliability. Some results of this method are also shown in this paper.

We are honored to be involved in the Shipping Lab project, http://shippinglab.dk/en/front-page/, where we have the opportunity to investigate the above-mentioned uncertainties. Such investigations are research-based and are not necessarily of a high priority investment in the shipping industry. Therefore, having the financial support from Shipping Lab and our partners is highly appreciated.

2. Influence of the source of speed and weather on performance indicators for hull and propeller

2.1. Case study 1

The vessel that is used here is a 81780 DWT bulk carrier, Table I.

Table I: Vessel properties

LBP	225.00 m
Beam	32.26 m
Scantling Draft	14.40 m
Scantling Deadweight	81780 tdw
MCR	9,660 kW

This vessel is equipped with a wave radar, which measures the waves and speed through water. The time series are filtered based on the following channels:

- Speed over ground
- Speed through water
- Ship heading
- Shaft RPM
- Power from torsion meter
- Wind speed & direction
- Wave height & direction

As explained in *Montazeri et al. (2019)*, the stationary periods are the periods, where all the above signals are simultaneously stable within certain criteria. This means that the mean value and standard deviation must remain the same over time windows that are considered. The theory of probability of detection of a change in the mean and standard deviation is utilized, *Lajic (2010)*. All physical parameters for stable period detection of different channels are normalized based on the vessel characteristics in the ship models. Therefore, the normalized parameters are now generic and can be used for different vessels. The mean deviation threshold and standard deviation thresholds are fine-tuned by analyzing the time series in the output. It should be noted that depending on the sampling rate of the input data and also depending on whether the data are instantaneous measurement or average values, those thresholds may need further adjustments.

In the recognized stable periods, the average of individual time series is calculated every 1 hour. The validation procedure of the data plays a significant role in autolog analysis. Specialized validation rule sets check the autolog data against various rules for the various detected stable periods. The validation output in VESPER shows no error for the range check of the above channels after filtration.

In this study, the weather from hindcast (provided by Weathernews Incorporated (WNI) is called for the corresponding way points and time stamps of the stable periods. The spatial resolution of hindcast data is 1.25° in the great circle distance and 6 hours in time. This may seem insufficient for our autolog analysis with sampling rate of 1 hour. Soon, WNI will provide higher resolution data which may change the detailed results of the analysis significantly. This weather data contains the current, the wind speed and direction and the combined wave height and direction. The analysis from hindcast is compared to the weather as reported by the vessel.

Added resistance is one of the major performance indicators in VESPER. This value represents the discrepancy between the actual power and the expected baseline power. The actual power is the reported power corrected for environmental conditions/weather. The difference between the actual power and the baseline is normalized as a friction coefficient. We present this value as a percentage of resistance coefficient at the reference speed (service speed) that is defined in the ship model. The added resistance trend indicates the level of fouling/damage on the hull and propeller over time since the last event on the vessel. The trend evaluation is started over, once an event/treatment is registered.

The data for 9 months are considered, and the added resistance is calculated based on different methods. First, we make a comparison between the speed over ground and speed through water and between ship-based weather and hindcast weather. The ship-based weather for autolog data means the anemometer for obtaining wind speed and direction and the wave radar for obtaining wave height and direction.

In this section, the criteria for reliability of performance trend is the trend reliability score, which is a built-in function in VESPER. This function takes into account the least square fit, the number of points and the slope to calculate the trend reliability. The more data points and the less scatter in added resistance, the higher prediction reliability is obtained.

2.1.1 Comparing different performance indicators for Noon data

First, we show the traditional noon-based results. The observation weather is taken from noon reports and includes wind speed and direction, estimated wave heights and direction. Table II shows the results. Based on the noon data, the results from logged speed (speed through water, STW) and observed speed (speed over ground, SOG) are very similar, considering the added resistance (AR) and the scatter (Least square fit, LSF). The value of log-factor, which is the ratio between speed over ground and speed through water is very close to 100% over the considered period. If we assume that the vessel in average is sailing in the same amount of current against and from behind, the speed-log can be considered to work properly, and we can use the speed through water for calculating the added resistance.

On the other hand, the added resistance based-on hindcast weather is 8-10% higher and the scatter is very similar to observed weather. The reason for the difference in added resistance due to using observed weather versus hindcast weather may be because the vessel in general is overestimating the weather and therefore achieves higher weather compensation than in the case of using hindcast weather. This observation, which is common in bulk carriers, is very important when evaluating the performance of a vessel, irrespective of noon data or autolog data. We elaborate on this comparison in the next section. The trend reliability score is higher than the observed weather as the number of points are higher. This is probably due to filtration when the vessel reports higher weather than hindcast. The data points, where the Beaufort numbers exceed 5, are filtered out in added resistance evaluation irrespective of vessel observation or hindcast.

Table II: Comparison between results of Added resistance for different data sources- Noon

Method	**Weather source**	**Valid reports**	**Estimation reliability Score**	**AR%**	**LSF of AR%**	**Log Factor %**	**LSF of Log Factor**
STW	Observation	91	94	2	11	99	3
	Hindcast	136	97	10	12		
SOG	Observation	103	94	9	12		
	Hindcast	144	96	19	14		

2.1.2 Comparing different performance indicators for Autolog data

Table II shows the results for autolog data for the same vessel and the same period. In this section, the STW is from the speed log. If we look at the added resistance based on the ship-based weather and speed over ground, it is 6% higher than noon data and the estimation reliability is slightly improved. Using the speed through water and ship-based weather gives a lower scatter and higher reliability, see Fig.2, than SOG, but the added resistance magnitude is not considered reliable. This is because the log factor trend has an unreasonable slope and it is different from the noon data, see Fig.1. The scatter (LSF) is also higher than the noon data for STW. Therefore, the speed through water from autolog gives a negative added resistance. Please note that the trends are calculated based on the P-Rate method which is a modified linear trend depending on the slope and scatter.

Table III: Comparison between results of Added resistance for different data sources- Autolog

Speed source	**Weather source**	**Valid reports**	**Estimation reliability Score**	**AR%**	**LSF of AR%**	**Log Factor %**	**LSF of Log Factor**
STW	Ship-based	789	99	-6	12	95	10
	Hindcast	1706	99	2	13		
SOG	Ship-based	880	95	15	16		
	Hindcast	1698	88	31	19		

As seen in Table III, in this case study, when we use the speed over ground for calculating added resistance, the hindcast weather is not as helpful as in noon data analysis as it increases the scatter and the added resistance is higher compared to noon data. The number of points in the hindcast analysis is twice the number of points from ship-based weather because, as mentioned before, bad weather filtration from anemometer or wave radar occurs more frequently than hindcast.

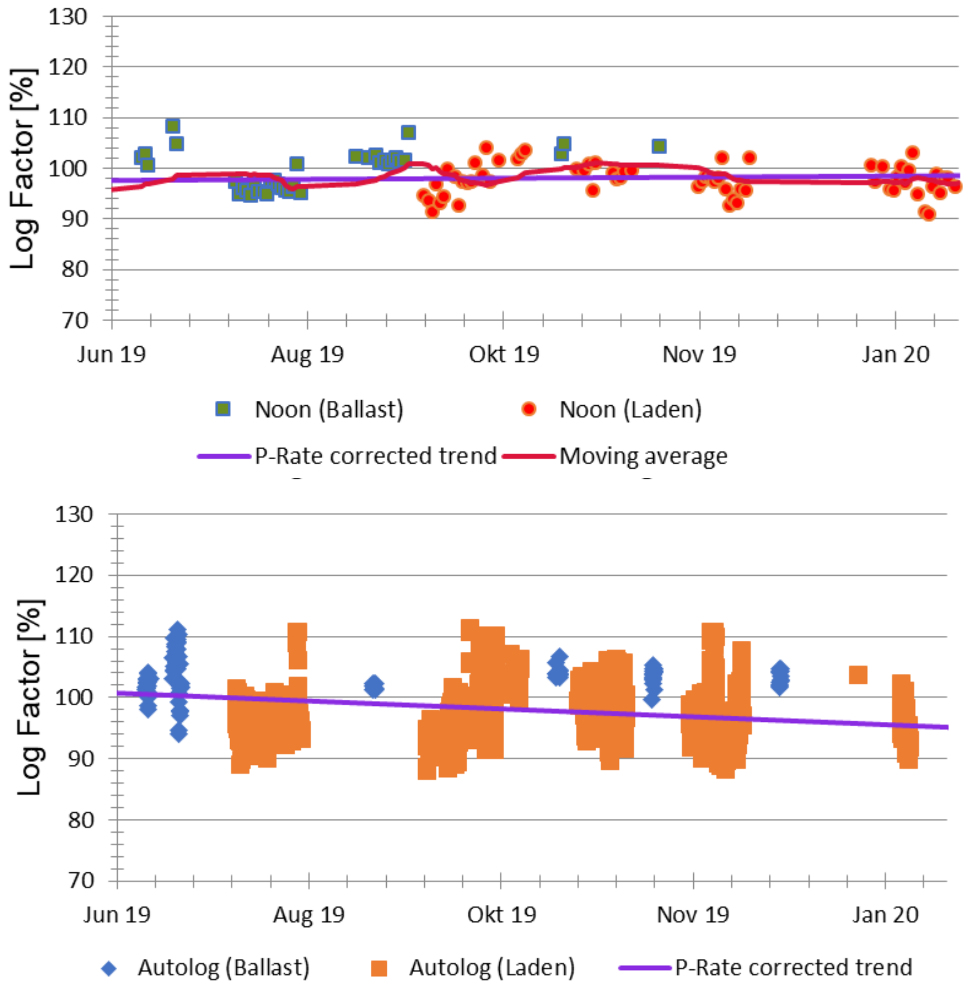


Fig.1: Log factor based on noon data (top) and autolog data (bottom)

2.1.3 Ship-based weather versus hindcast

In Figs.3 and 4, for the same event period as Sec. 2.1.2, we compare the weather from hindcast and from the ship-based tools after the stable period detection. The distributions of wind speed and wave height are shown, respectively for both sources. The two distributions (ship-based and hindcast) at mild sea and very rough sea are quite close but a considerable difference can be observed in moderate sea condition. This difference is more significant in wind speed distribution.

As mentioned before, the hindcast weather is milder than the ship-based weather. This confirms the above-mentioned assumption that the data points that are filtered out in ship-based weather are more probable than in hindcast weather, because in many way points the ship-based weather shows Beaufort Numbers above 5 (above 11 m/s wind speed and 2.5 meter wave height) whereas the hindcast shows Beaufort 4.

It is noteworthy that we cannot certainly prefer one method over the other. Anemometer is not believed to be the most accurate tool to measure wind. On the other hand, hindcast model could also be inaccurate especially due to the lower resolution than our autolog dataset as discussed before. Nevertheless, using the reliability evaluation and all the above comparisons, it can be concluded that the wave radar and anemometer are more trustworthy than hindcast in this specific case study.

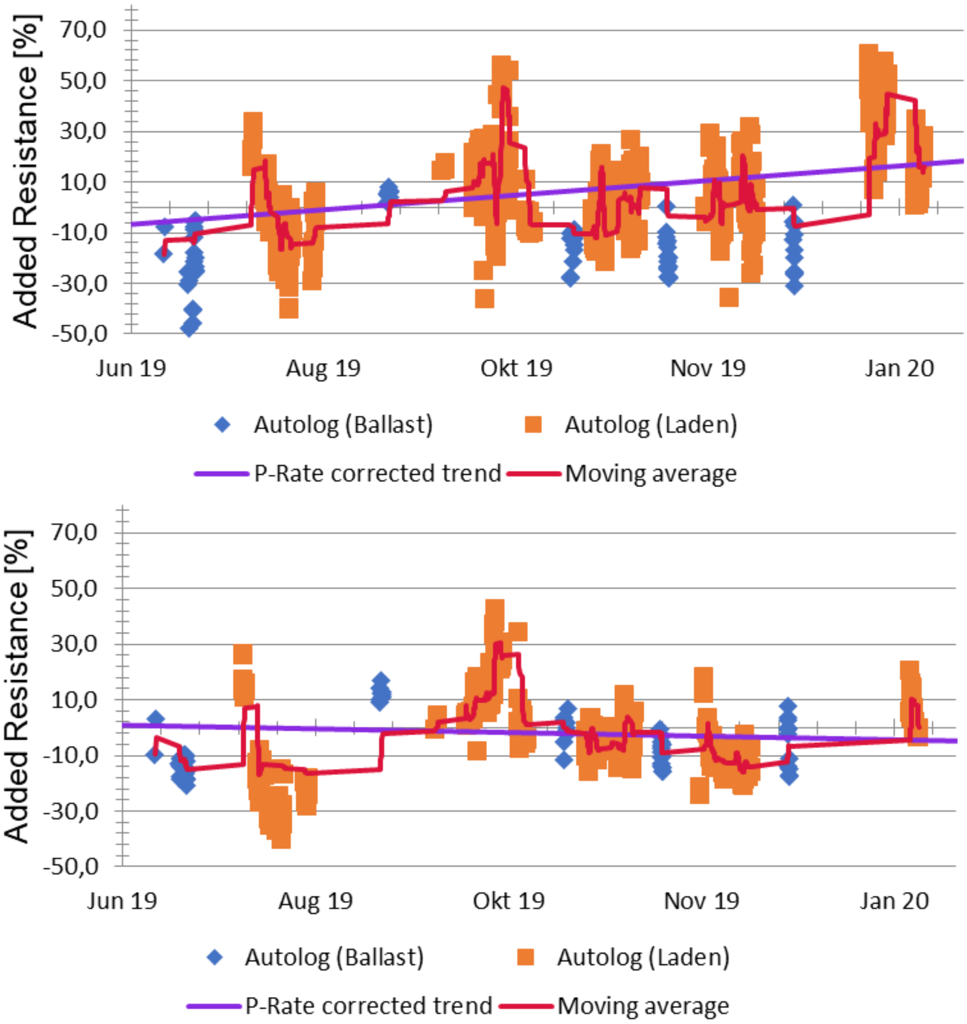


Fig.2: Comparison between using SOG (top) and STW (bottom) in calculating added resistance (Autolog)

2.1.4 Different methods to calculate speed through water

In this section, we investigate the speed through water as input to the performance indicator calculation. The speed through water is obtained based on 3 different sources. Method 1 is defined by using the speed log in the autolog time series (as shown in the previous section). Method 2 is to use the current from hindcast and calculate the speed through water based on the current plus the speed over ground. Finally, the last approach, method 3, is to use the speed through water from wave radar.

In Table IV, the results for the 3 above sources of speed through water are compared. It is obvious that the log factor is estimated to the same level (95%) using the different speed sources. Using the radar-based speed through water instead of speed log, the added resistance value and the scatter remains the same.

Considering all the above discussions in Sec. 2.1, it can be realized that choosing the best performance indicator out of the different methods is not easy and straight forward. The combination of speed log from noon data and hindcast seems to be reliable. So, 10 could be a good estimation of added resistance at the end of the period. The added resistance from SOG in autolog data and ship-based weather is 15. This method, among the different approaches above, can be considered as the best autolog method in this case study.

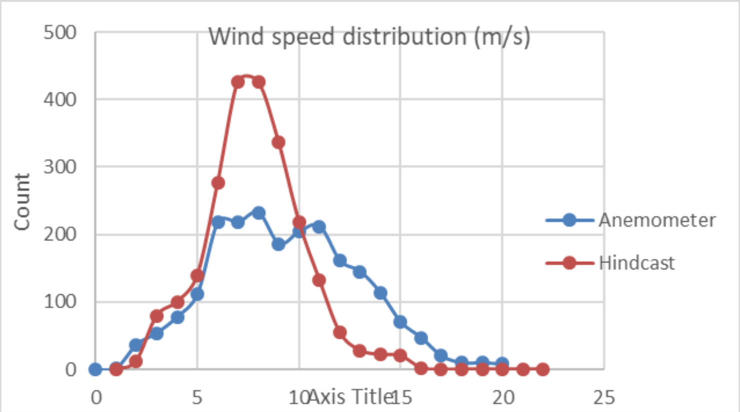


Fig.3: Wind speed distribution from hindcast and anemometer

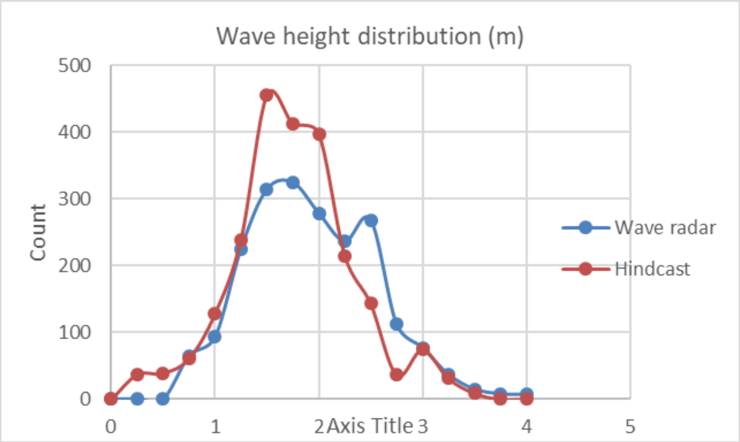


Fig.4: Wave height distribution from hindcast and wave radar

Table IV: Comparison between results of Added resistance for different data sources

Source of STW	**Weather source**	**Valid reports**	**Estimation reliability Score**	**AR%**	**LSF of AR%**	**Log Factor %**	**LSF of Log Factor**
Speed log	Anemometer and wave radar	789	99	-6	12	95	10
SOG corrected by Hindcast Current	Hindcast	1804	87	29	19	95	10
SOG corrected by Wave Radar Current	Hindcast	1748	87	29	19	95	10
SOG corrected by Wave Radar Current	Anemometer and wave radar	812	99	-7.2	12	95	10

The STW based on the current from hindcast results in a similar log factor but the hindcast weather gives less reliable added resistance compared to ship-based weather, as in the previous section.

2.2. Case study 2

The second vessel's characteristics are shown in Table V. The same procedure is applied on this vessel and the results are shown in Tables VI and VII. Compared to the previous ship, the amount of data that are available in the event period (4 months) is less. Moreover, no wave radar is installed on this ship, so the ship-based weather is coming from anemometer only. The waves are estimated according to the wind data.

Table V: Vessel properties

Property	Value
LBP	222.00 m
Beam	32.26 m
Scantling Draft	14.40 m
Scantling Deadweight	81500 tdw
MCR	9700 kW

2.2.1 Comparison between results of Added resistance for different data sources

Tables VI and VII show the performance indicators for this vessel based on noon data and autolog data, respectively. For noon data, similar to Table II for the previous case study, the trend reliability of added resistance based on hindcast weather is higher than observation weather. However, the log factor magnitude shows that the speed log needs a calibration. Therefore, the added resistance based on STW is 15% lower than SOG method.

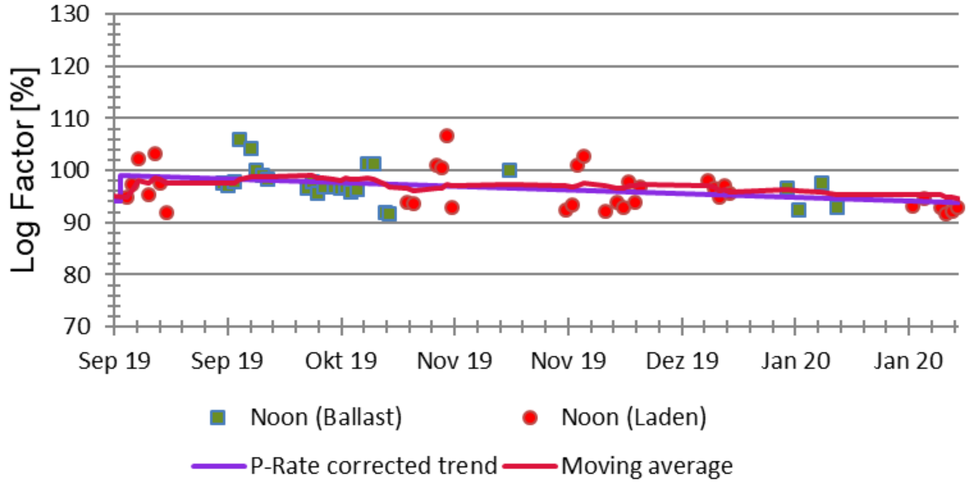
Table VI: Comparison between results of Added resistance for different data sources - Noon

Speed source	Weather source	Valid reports	Estimation reliability Score	AR%	LSF of AR%	Log Factor %	LSF of Log Factor
STW	Observation	47	74	4	11	95	3
	Hindcast	49	88	0	9		
SOG	Observation	50	51	10	16		
	Hindcast	49	61	15	14		

Table VII: Comparison between results of Added resistance for different data sources - Autolog

Speed source	Weather source	Valid reports	Estimation reliability Score	AR%	LSF of AR %	Log Factor %	LSF of Log Factor
STW	Anemometer	561	89	4	14	96	4
	Hindcast	580	99	0	14		
SOG	Anemometer	576	91	11	11		
	Hindcast	569	98	9	13		

The autolog data in Table VII shows very similar results as noon data for trend values of added resistance and log factor. Although the log factor is still 4% off, the log factor slope, Fig.5, is more consistent than the previous case study, Fig.2. Compared to noon results, the estimation reliability in autolog results has increased significantly due to the very larger number of points. It can be concluded that in this case study, the hindcast weather and SOG gives the most reliable results. Contrary to our expectation, the results of STW indicates a higher scatter. In the next section we focus more on this issue.



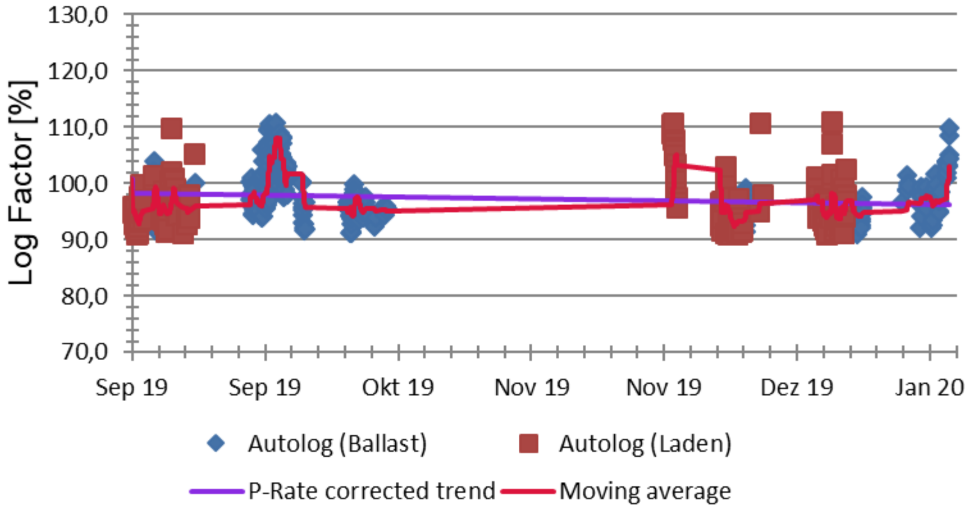


Fig.5: Log factor based on noon data (top) and autolog data (bottom)

2.2.2 Measurement of speed through water

A well-functioning speed log is a fundamental source for speed since it measures speed through water and therefore not affected by current set and drift. A well calibrated speed log can give accuracies of up to 0.1%, but since it is sensitive to a number of factors, the variation in measurements can be high.

In this case study, as seen in Table VII, the speed through water increases the scatter of added resistance. In Fig.6, the trend of added resistance is considered in a short period basis speed over ground and speed through water. In laden condition, yellow marks, the scatter in STW method is decreased by almost 50% whereas in the ballast condition, the blue marks, the STW method scatter is larger than SOG method.

Sea state conditions combined with variations in loading conditions (draught, trim and list) can cause large variations and offsets in the measurements. The actual current profile and water depth has an impact depending on the speed log type. Therefore, using the speed from the speed log in performance analyses should be considered with care and by applying filtration of data to comparable conditions.

For the STW from wave radar, some of the variations due to the above-mentioned conditions in the speed log are expected to be eliminated since there are no subsea installations. However, the wave radar would need waves to function, therefore it does not give speed through water in calm seas. In the case study in Sec. 2.1.4, the results from wave radar were similar to the ones obtained by the speed log. More datasets need to be analysed to get a better idea of advantages and disadvantages of both methods.

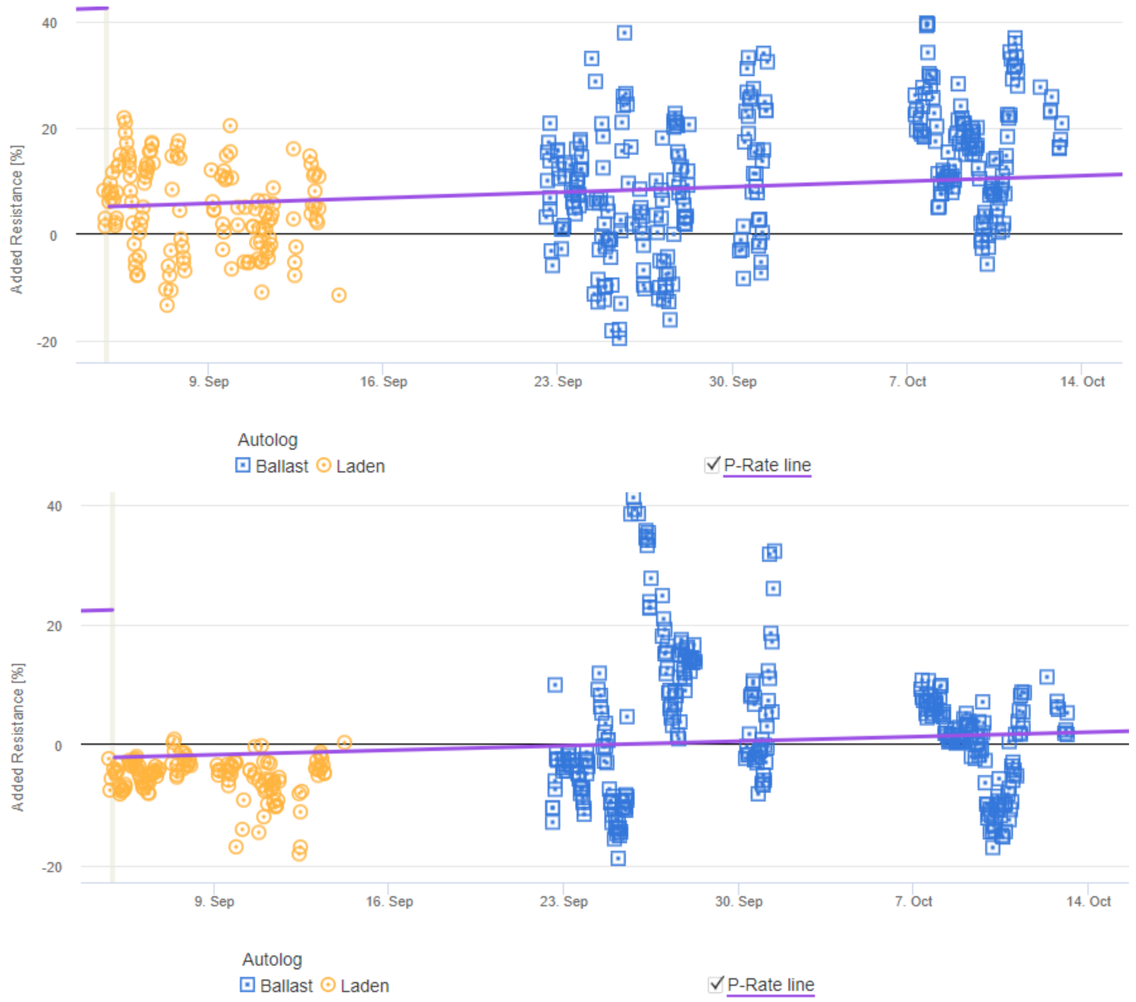


Fig.6: Added resistance based on SOG (top) and STW (bottom)

3. Confidence Interval for different weather sources

As mentioned before, the current method for evaluation of trend reliability in VESPER platform is based on an in-house function combining the LSF error around the trend line, the slope of the line and the number of points. All reasonable dependencies and the methods have been fulfilling its purpose for a long time. However, the method needs to be further refined for evaluation of performance indicators in the future. In order to do this, VPS is currently implementing a more consistent method based on sound statistical principles.

In this section, the reliability measure is therefore considered by looking at the confidence interval among the time trend of the added resistance. This method, thanks to Prof. G. Chen (Aalborg University), establishes the confidence interval at the end point of the added resistance trend line to evaluate the reliability of the trend calculation.

In Fig.7, the results between autolog and noon for vessel 2 (Sec. 2.2) are compared over the same period. As observed in these charts, the trends between the 2 methods are similar but the confidence level of the trend, at the end of the period, in autolog results has improved from ±8.6% to ±2.1%.

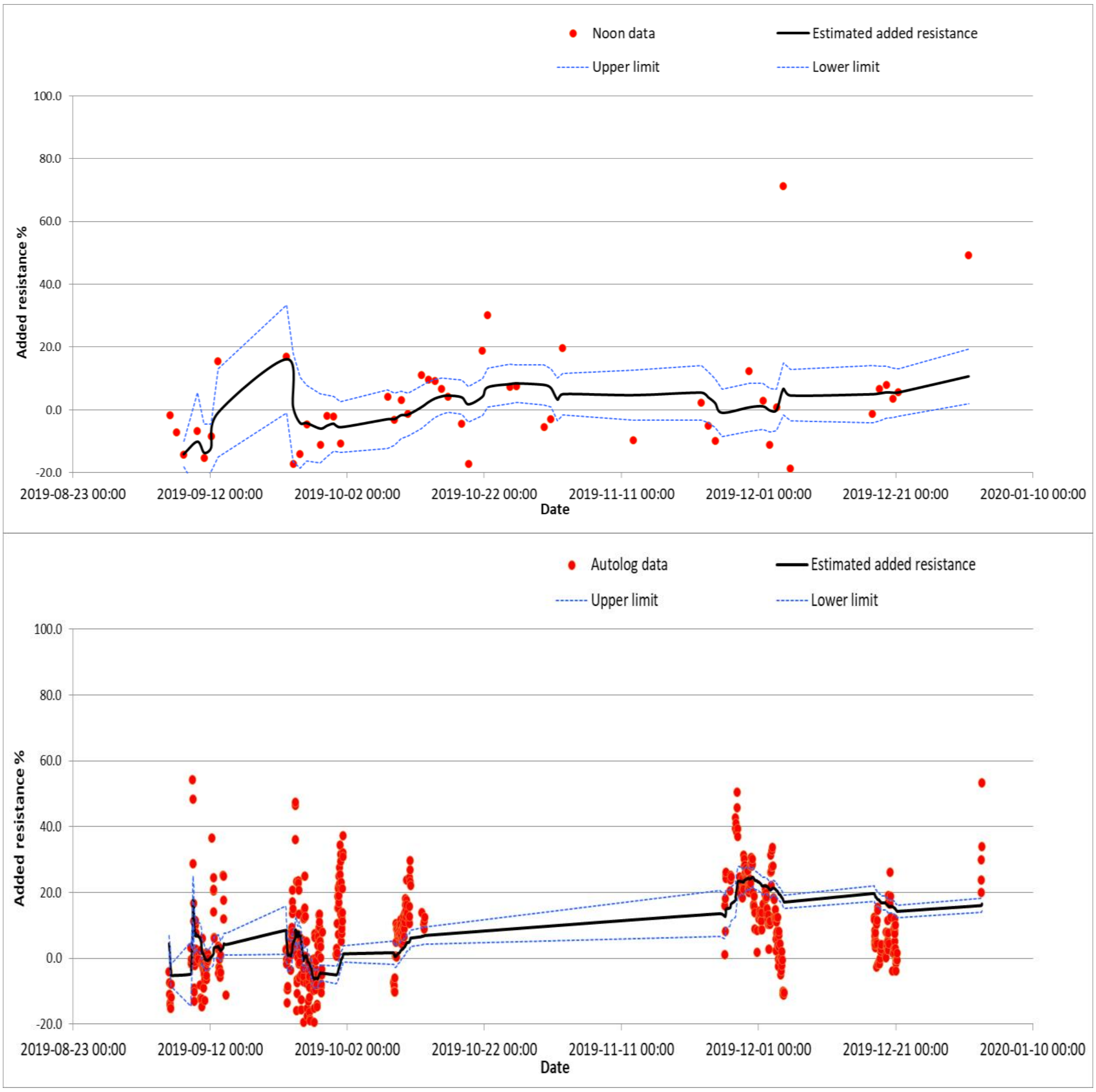


Fig.7: Confidence interval for added resistance based on noon results (top) and autolog results (bottom)

4. Summary and Conclusion

This paper shows some results based on the autolog-based tool that is developed in VESPER (The performance analysis software by VPS). The goal is to investigate how the autolog data can be utilized for performance analysis. Prior to make this method operational, a lot of research needs to be carried out to get a good control of sensor errors, sensor drifting and modelling errors.

Two bulk carriers were studied within the "ShippingLab" project. The parameters for filtration procedure are normalized by ship characteristics, but manual fine-tuning of some of the parameters is still required as an automatic parameter optimization has not been developed yet.

The added resistance due to fouling is estimated based on the filtered autolog data. From the case studies so far, it can be observed that the method of stable periods is superior to noon data as the estimation reliability is improved. Confidence interval is now implemented to evaluate the reliability of estimations for performance indicators.

The conclusion from the studies so far shows that if the speed through water is measured correctly, it gives more consistent results of performance indicator than the speed over ground.

The present form of the available hindcast data shows milder weather than the autolog weather. Therefore, the added resistance for the 2 methods is not always consistent and the hindcast weather with current resolution does not always improve the added resistance reliability. As mentioned before, this is expected to improve significantly when the hindcast data become available in a much higher resolution.

VPS has been receiving many autolog datasets from different shipping companies. We will continue the work for further investigation of autolog-based performance analysis and also improvements of modelling in VESPER. We still believe that noon data will stay as a basis for performance management systems in the shipping world for a long time. However, we consider that a combination of noon data and automated data and thereby, enriching the performance estimations is the best solution going forward.

The challenge will be to see through the cloud of many different data entries that all can be used to predict vessel performance but not necessarily providing the same results. The goal will then be how to dynamically select the ones that will provide the closest result to the actual real performance of the ship.

References

LAJIC, Z. (2010), *Fault-tolerant onboard monitoring and decision support systems*, PhD thesis, DTU Denmark, Lyngby, pp. 50- GLR test- variance change

MONTAZERI, N.; PETERSEN, J.B.; HANSEN, S.V. (2019), *Autolog data processing for vessel performance application*, 4th HullPIC Conf., Gubbio

Accurate Voyage Sea State and Weather Measurements Improve Performance-Based Vessel Management

Vemund Svanes Bertelsen, Miros, Asker/Norway, vsb@miros-group.com
Rune Gangeskar, Miros, Asker/Norway, rg@miros-group.com
Gunnar Prytz, Miros, Asker/Norway, gp@miros-group.com
Michael Schmidt, BW Dry Cargo ApS, Copenhagen/Denmark, michael.schmidt@bwdrycargo.com

Abstract

The latest generation radar-based sensing solutions provide all relevant stakeholders with high-quality information about key vessel voyage parameters such as Speed Through Water (STW), ocean surface currents and wave height, direction and period. This information can now be readily made available both onboard and onshore in real-time. A wide range of vessel performance applications can achieve significant improvements using this information. This paper will describe how the availability of accurate sea state data is of significant value for vessel chartering management. Contractual weather claims can be handled better with more accurate weather data along the vessel route. Furthermore, benchmarking of vessels can be made more accurate when based on high-quality sea state data. In addition, accurate sea state data can unlock cost reductions due to better insights into the physical conditions along the vessel route and therefore better separate effects of weather and actual vessel performance. This can in turn result in significantly reduced vessel fuel consumption. The various use cases will be discussed here together with some examples from testing on vessels.

1. Introduction

Most industrial domains are currently in a process of digital transformation. This holds true also for shipping where a wide set of data from many sources is utilized to gain insight into all aspects of the operation of vessels. Vessel performance optimization has become a hot topic in the area of digitalization, fueled by the fact that shipping contributes to a significant amount of the global air pollution of substances such as sulfur dioxide, nitrogen oxide and particulates as well as to global emissions of carbon dioxide.

The rapid development of new relevant technologies means that new possibilities are made available to support the strong focus on cost reductions and operational efficiency. In order to succeed with digitalization initiatives, there is a need to address significant pain points experienced by the various business stakeholders. These pain points need to be solvable with the use of a combination of high-quality data and data science. Another prerequisite is a suitable platform to both collect the data, process the data, present the results to the users or integrate with external systems. All of this requires a high degree of competence on the various technologies, how to get insight out of vast amounts of data, how vessels are operated and how the various business stakeholders interact.

There is a wide range of data that is relevant for the various use cases and challenges found within vessel performance management. This includes data from a vast array of sensors on a vessel, information about the vessel itself, route information, destination information, weather and sea state information, contractual information and financial figures related to the vessel, charter and fuel.

A crucial data point is the vessel Speed Through Water (STW) which is the vessel speed relative to the water. STW is equal to the Speed Over Ground (SOG) when there is no ocean surface current present. STW can be seen as a measure of the output a vessel produces given a certain input of fuel, loading condition, vessel configuration and sea state. Without accurate data on STW it is not possible to accurately determine the performance of a vessel. Consequently, the lack of accurate STW data is a major obstacle to progress in vessel performance management. Some of the resulting challenges are:

- Difficult to evaluate hull and propeller designs
- Difficult to evaluate the efficiency of hull coatings
- Difficult to evaluate the efficiency of hull and propeller cleaning procedures
- Inaccurate hull performance estimations and resulting suboptimal maintenance planning
- Limited insight into how sea state influences performance at various combinations of vessel speed, trim and draft
- Difficult to accurately determine performance relative to contractual agreements
- Difficult to do accurate and reliable voyage optimizations
- Difficult to do speed optimization

SOG is easily measured by means of a GPS receiver. STW, however, has not been easily measured in an accurate and reliable way until recently, *Gangeskar (2019)*. STW is important since the currents experienced by vessels on the world's oceans are significant and can range up to several knots in magnitude. Models used by weather providers to forecast current patterns are based on coarse grids, they lack input of accurate surface current measurement data and cannot accurately predict conditions in space and time. Thus, there is a need for accurate current and STW data.

There have been significant improvements within radar-based sea state measurements recently *Gangeskar (2017,2018a,2019), Gangeskar et al. (2018)*. The latest solutions in radar-based sea state measurements can measure both ocean waves and ocean currents accurately under widely varying conditions and with high availability, reliability and accuracy.

Both ocean waves and ocean currents have a significant impact on ship performance. The interaction between waves and ship performance is quite complex and requires accounting for factors such as 3D hull properties and loading conditions. The interaction between surface current and ship performance is somewhat simpler. Currents coming against the direction of ship motion means that more water needs to be displaced per time unit compared to a situation with no current. Similarly, currents travelling in the direction of ship motion means that less water needs to be displaced per time unit. Hence, the current component going in the direction parallel or antiparallel to the vessel heading has a major influence on vessel performance. Currents travelling perpendicular to the ship motion might also lead to a need to spend energy to counter the forces inflicted by the currents. Thus, the presence of ocean currents has a profound influence on the performance of the vessel.

Measurements of ocean surface current from moving vessels by traditional underwater (in-situ) instrumentation are associated with challenges. Data is heavily influenced by noise, and systems measuring the speed through water (STW) are influenced by similar disturbances affecting the vessel speed log, *Antola et al. (2017), Baur (2016), Bos (2016), Fritz (2016)*. Wave measurements from fixed underwater instrumentation are scarcely available. The following items are relevant for both acoustic Doppler current profilers (ADCPs), *Flagg et al. (1998), King et al. (1993), New (1992),* and other instruments based on traditional in-situ measurement principles:

- Underwater equipment is exposed to fouling, *Carchen et al. (2017), Goler et al. (2017), Kelling (2017).*
- Measurements are disturbed by air bubbles, turbulence, and inhomogeneous hydrodynamics caused by the vessel motion and propellers, *Bos (2016), Carchen et al. (2017), Brown et al. (2001).*
- Measurements are disturbed by other instruments, for instance acoustic echo sounders and vessel speed logs.
- The surface current measurements are considerably affected by the vessel movement.
- Sensors are frequently inadequately calibrated, *Antola et al. (2017), Bos (2016),* giving systematic errors in certain speed ranges, *Antola et al. (2017).*
- Underwater equipment generally involves installation and maintenance procedures being both time-consuming and expensive.

Most vessel performance management applications will benefit from accurate STW measurements. One example is hull (and propeller) performance where the amount of fuel consumed at a given speed is analyzed. Hull fouling will lead to increased friction and consequently increased fuel consumption at the same speed, or, alternatively lower speed at the same fuel consumption. Presently, hull performance estimates are typically based on SOG measurements from a GPS or heavily filtered STW measurements from underwater, hull-mounted sensors. Hull cleaning is an expensive procedure and it is therefore important to estimate the actual hull condition as accurately as possible. Accurate STW measurements can be used to improve hull performance estimations and can lead to improved planning of hull cleaning activities. Similarly, accurate data can be used to investigate the effectiveness of hull cleaning procedures or hull coatings.

There are several vessel performance management use cases related to handling of performance guarantees and weather claims. The charterparty concept is crucial in this context. A charterparty is a maritime contract between a shipowner and a "charterer" for the hire of a ship for the carriage of passengers or cargo.

A charter party normally includes a performance clause, guaranteeing a maximum fuel consumption at one or two speeds in loaded condition. The performance clause is warranted in fair weather conditions, described by a maximum wind force, sea state and no current.

For a ship owner and an operator trading a ship under a charter party, it is crucial to know the ship's actual speed vs. fuel consumption performance. Furthermore, it is important to know the exact wind force, sea state and surface current conditions to determine whether the vessel is operating within or outside the weather conditions defined in the charter party. If the wind force, sea state and surface current conditions are lower than the limits defined in the charter party, for more than 18 hours of a day, the day is deemed a "Good Weather Day". In this case the ship has to meet the warranted speed/fuel consumption described in the charter party. Underperformance in terms of lower speed and/or excess fuel consumption has to be compensated by the ship owner or operator to the charter. If the wind force, sea state and surface current conditions are above the limits defined in the charter party, for more than 18 hours of a day, the day is deemed a "Bad Weather Day" and the ship need not meet the warranted speed/fuel consumption described in the charter party.

In such a setting it becomes crucial to not only have high-performing efficient vessels, but also to be able to accurately monitor the environmental conditions. For both the ship owner or operator and the charterer, it is important to accurately measure the environmental conditions, so that it can be precisely determined when the conditions are within the charterparty limits. Equally important for both parties is to have vessels that are both high-performing and cost-efficient. Therefore, accurate and reliable information about vessel performance makes it easier for charterers to select the best performing vessels for the job. For vessel owners and operators with efficient vessels this represents an additional value that will be attractive to prospective customers.

While wind information has been readily available, it has been more challenging to measure wave and current conditions. With the recent technology development from Miros it is now possible to have access to both wave and STW measurements that are reliable and accurate enough to be used in vessel performance management, *Gangeskar (2018,2019)*. This information can easily be made available both onboard the vessel and onshore in real-time through the usage of modern IoT technologies, Prytz et al. (2019).

This paper presents a description of the system that provides reliable wave and STW measurements, based on an imaging X-band radar, results from a verification study onboard a vessel and how applying onboard measured data could reduce some key challenges associated with determining "good weather".

2. Measurement principle for waves and STW based on imaging X-band radar

Wavex bases its measurements on radar images covering local areas of interest, in a reasonable distance from any disturbing structures, including the vessel hull. Fig.3 shows how measurement areas are extracted from the radar images for current and STW measurements. Measurement areas for waves are extracted in a similar manner. The measurement areas are called Cartesian image sections and are defined during system commissioning through software configuration. Dedicated algorithms process these images to provide the user with real-time wave spectra, as well as integrated wave parameters, surface current vectors and STW data.

Optimum wave and STW measurement performance require radar images with sufficient spatial resolution. The radar's range resolution is determined by the radar pulse width, and the azimuth resolution is determined by the radar antenna beamwidth. For optimal accuracy, the radar should be operated in short pulse mode. (If a solid-state X-band radar, utilizing pulse compression techniques, is used, the spatial resolution in the STW measurement area can be sufficient without compromising the radars navigation performance.) In addition, a wind speed of at least 2 – 3 m/s is required. At this wind speed, the sea surface gets sufficiently rough to create sufficient electromagnetic backscatter, *Skolnik (1980)*. Gravity waves modulate the ocean surface backscatter. A radar image with a clearly visible wave pattern is shown in Fig.2.

Wavex provides current measurements with high accuracy, *Gangeskar (2018a,b,c), PRYTZ et al. (2019)*. Measuring the STW has much in common with measuring currents, and the two measurements are generally based on the same physical principles. The major difference is what the measured water speed is referred to: the vessel when measuring the STW, and a fixed position when measuring currents.

The vessel's velocity through water and current velocity are related through:

$$\vec{\boldsymbol{v}}_{\boldsymbol{STW}} = \vec{\boldsymbol{v}}_{\boldsymbol{SOG}} - \vec{\boldsymbol{U}}, \tag{1}$$

Here $\vec{\boldsymbol{v}}_{\boldsymbol{SOG}}$ is the vessel's velocity over ground. Therefore, obtaining reliable current measurements implies that also STW measurements will be reliable, as they are related to each other (at the same depth) through the speed over ground (SOG), which can easily be extracted from GPS data.

Fig.1 shows the basic components in a Wavex system on a moving vessel. Specialized, DNV type approved hardware is connected to the analog video signal output from a marine navigation X-band radar. This hardware digitizes the analog radar video and outputs a radar image timeseries. Each radar image includes a sector covering the STW measurement area. Digitized images can also be acquired directly from radars with digital data output, commonly known as IP (Internet Protocol) radars. This eliminates the need for additional digitalization hardware.

The Wavex system requires certain radar image meta-data from a GPS and a gyro compass.

To provide STW estimates, all required data are collected, synchronized and processed on the system computer.

For further details on how Wavex measures wave, current and STW, refer to *Gangeskar et al. (2018)* and *Prytz et al. (2019)*.

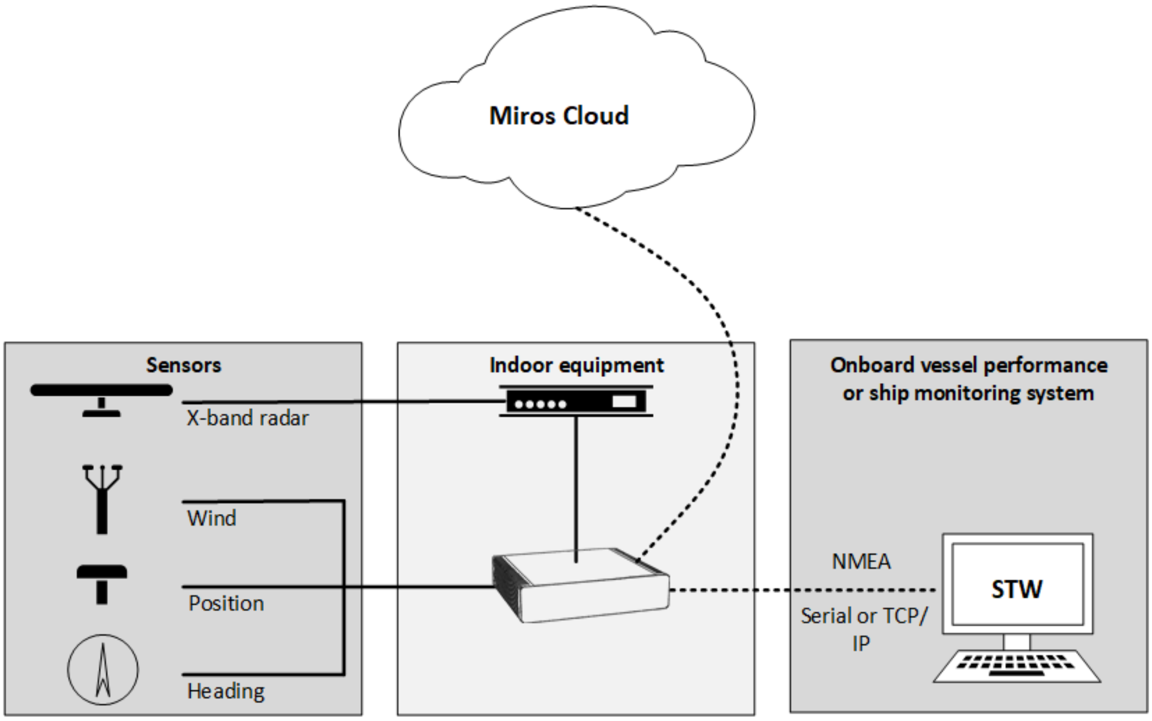


Fig.1: Schematic diagram of system based on imaging X-band radar

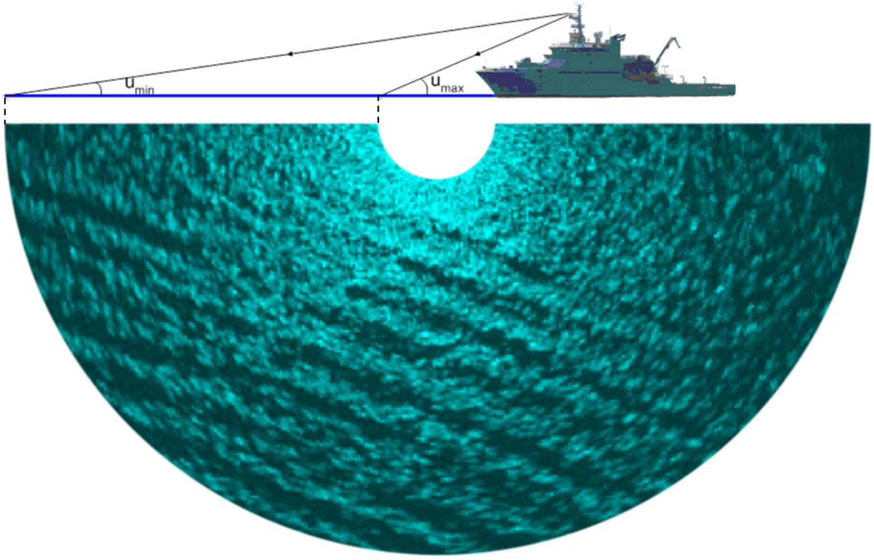


Fig.2: Imaging radar

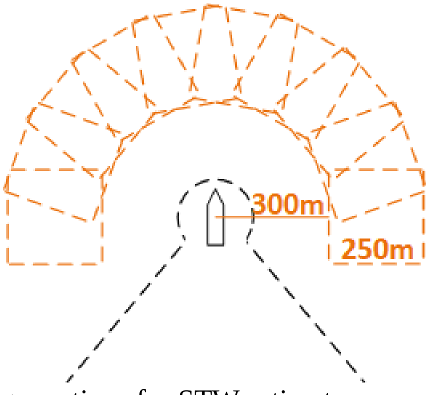


Fig.3: How Cartesian image sections for STW estimates are extracted from a radar image

3. Pilot verification of STW, current and wave measurements at BW Rye

Wavex pilot systems have been installed on various vessels using various types of imaging X-band radars. The system reliability and the accuracy of radar-based STW measurements have been examined and verified by comparing the measurements with theoretical models and standard speed logs over large geographical areas in a wide range of weather conditions and sea states, *Gangeskar (2018a,b,c, 2019)*. Wave measurement accuracy was discussed in *Gangesakr (2017)*. The verifications performed at the dry cargo vessel BW Rye will be presented and discussed here.

3.1. Data acquisition

The following results are based on data acquired from the cargo vessel BW Rye. Data from the Miros Wavex and additional on-board sensors have been acquired during four voyages from March 2019 to June 2019, and they are compared with model data from the voyage reports provided by a well-known weather provider. Fig.4 shows the routes during voyage 1, 2, and 3, based on positions acquired from the on-board GPS and stored in the Wavex system. Fig.5 shows the route during voyage 4. Due to the vast amounts of data, the timeseries plots presented are limited to a period in voyage 4.

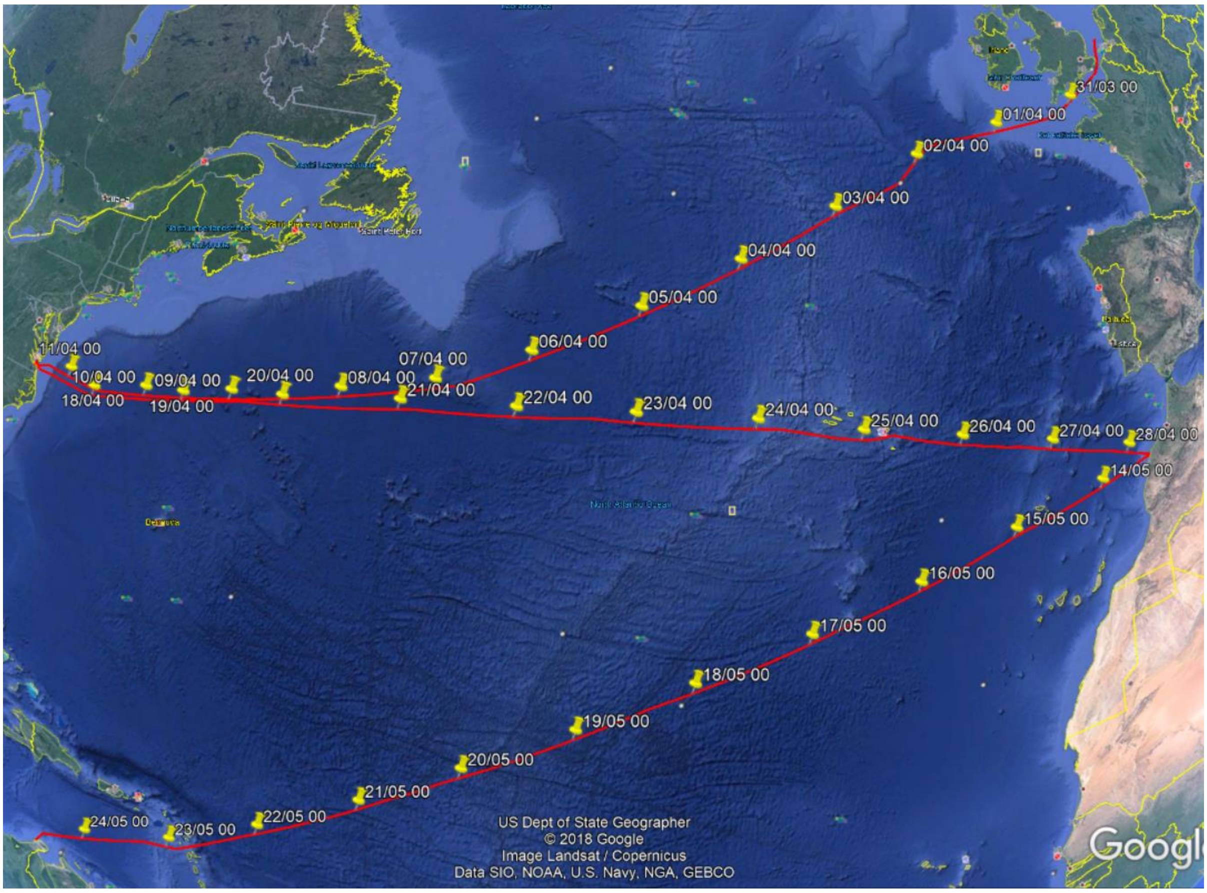


Fig.4: Map exported from Google Earth showing routes during voyage 1, 2, and 3, crossing the Atlantic Ocean westwards, eastwards, and westwards, respectively, indicated by red lines.

The electromagnetic speed log on BW Rye is an EML500-HV1 from Yokogawa Denshikiki Co. Ltd. Speed log data together with data from the onboard GPS and gyro equipment were sampled every 30 and stored to a file for later analysis.

BW Dry Cargo provided voyage reports (PDF files) including model data typically sampled every 6 hours. The directional resolution of current model data was 22.5°, meaning that the specified 10°

accuracy of Wavex current measurements cannot be validated based on these data. In addition, unfortunately, a major part of the model data relates to positions that are from several kilometers to more than twenty kilometers away from the vessel, making comparison with unaveraged measurements less reasonable. The large position deviations are probably caused by coarse data grids in the models.

Fig.5: Map exported from Google Earth showing route during voyage 4 around the South American coast, indicated by red lines.

3.2. Longitudinal current and speed components

The longitudinal water speed was acquired directly from the speed log data files. Longitudinal speed and current components were easily deduced from Wavex complete STW and current vectors. Comparable model data were calculated based on current speed and direction from the voyage reports, using vessel heading data from the on-board gyro logged in Wavex data files. Current longitudinal components from the speed log were obtained by converting the STW longitudinal component using equation (1) and data available from the speed log data files.

Fig.6 shows longitudinal current and STW components during a part of the voyage around the South American coast. All available data are shown, with no additional averaging in the upper and lower parts of the figures. The middle part of the figures, however, show longitudinal current components after applying an additional centered averaging to Wavex and speed log data, making a total averaging time of 6 hours. The indicated average levels, one measured level for every model data point, make a reasonable way of comparing measured data to model data, as the model data typically have an update period of 6 hours and further analysis typically is based on such 6 hours' values. Hence, the significance of having available measurements rather than model data can be observed, as well as the potentially additional value of getting real-time updates every minute. During periods with rapid changes, as can be seen in the figures, 6 hours update period may be too slow, depending on the application of interest.

As already mentioned, only a part of the model data refers to positions close enough to BW Rye to make comparison of unaveraged current data sensible. Data points within 2 km distance from BW Rye are indicated with black markers in Fig.6, and the remaining points with grey markers. Model data tend to agree more with measurements when considering 6 hours' values during periods with relatively stable currents over large areas, probably because model accuracy becomes better when position and time are less important and when local fluctuations are negligible. Apart from these stable situations, model data often seem to fail to correctly render temporal and spatial variations that are captured by both Wavex and speed log, resulting in only a moderate correlation with measured data. This is also indicated by the statistics in Table 1 and scatter plots in Fig.7, comparing 6 hours' average data from Wavex and speed log with model data. The total averages over all voyages from Wavex and model data agree fairly well, as indicated by the mean deviation in Table 1. Mean deviations based on the speed log are, however, less accurate due to offsets discussed below. Correlations between model data and measured data are moderate, whereas the correlation between the two very different sensors is strong, as discussed below.

When comparing model data with measurements, it should be kept in mind that such model data typically provide rough overviews of environmental data on a large scale in space and time. Measurements, however, can provide representative data for the local area of interest, in real-time or as average values, and with a higher accuracy than model data. Furthermore, measurements are required as input to models to get reasonable output from models.

From the current time series in the upper part of the figure below, it is evident that the radar-based system produces considerably smoother data than the speed log. The reason for the varying amounts of noise observed in speed log data is not known. The speed log data are also influenced by offsets, particularly during voyages 2 – 4, where slowly varying offsets can be observed as negative longitudinal current components (in the opposite direction of the vessel heading) in the typical range of 0.3 to 0.8 m/s. A closer look at any of the voyages tells us that these apparently considerable current contributions are not physically reasonable. For instance, during voyage 2, the speed log measures a considerable current contribution towards west, lasting for more than one week of the voyage, which is not physically reasonable when travelling in these parts of the Atlantic Ocean. One might, however, observe a smaller contribution towards east due to the Gulf Stream and the North Atlantic Drift, though this is probably not measurable unless travelling on a slightly more northern path. Also, note that model data comply well with Wavex data during this last week of voyage 2, when the longitudinal current component is quite stable and close to zero over a large area.

An additional indicator of the speed log offset is the long-term average value of the longitudinal current component, which is expected to approach zero as the amount of considered data increases, provided that there is no systematic offset introduced by for instance always following the larger ocean currents around the world. This average value is -0.39 m/s for the speed log when considering all voyages together, whereas the corresponding value from Wavex is only 0.02 m/s.

Erroneous offsets, like the one observed in the speed log data, can frequently be observed in data from traditional speed logs due to inadequate calibration, as have also been found during previous work on validating STW measurements. The statistics in Table I include the mean deviation (offset) between speed log and Wavex based on all available data (voyage 1 – 4) and no additional averaging, as well as the root-mean-square (RMS) and the standard deviation between the two sensors. The corresponding scatter plot is provided in Fig.7, including a Deming regression (parameters in Table 1), which was preferred to simple linear regression because it accounts for errors in both sensors. As mentioned above, however, the speed log offset is slowly and gradually changing, meaning that the offset is not a constant that can be compensated for when considering all data together. This offset drift can be vaguely seen in the scatter plot in Fig.7 as if the plot consists of several clouds with different offsets.

Despite varying amounts of noise and offsets, the agreement between the speed log and the Wavex is very good when it comes to trends in the time series. This is also supported by correlation coefficients in the range 0.84 – 0.97. By removing the offsets between the two sensors, RMS deviations in the range 0.12 – 0.19 would be obtained for the four voyages, which could be further reduced by noise-filtering the speed log data.

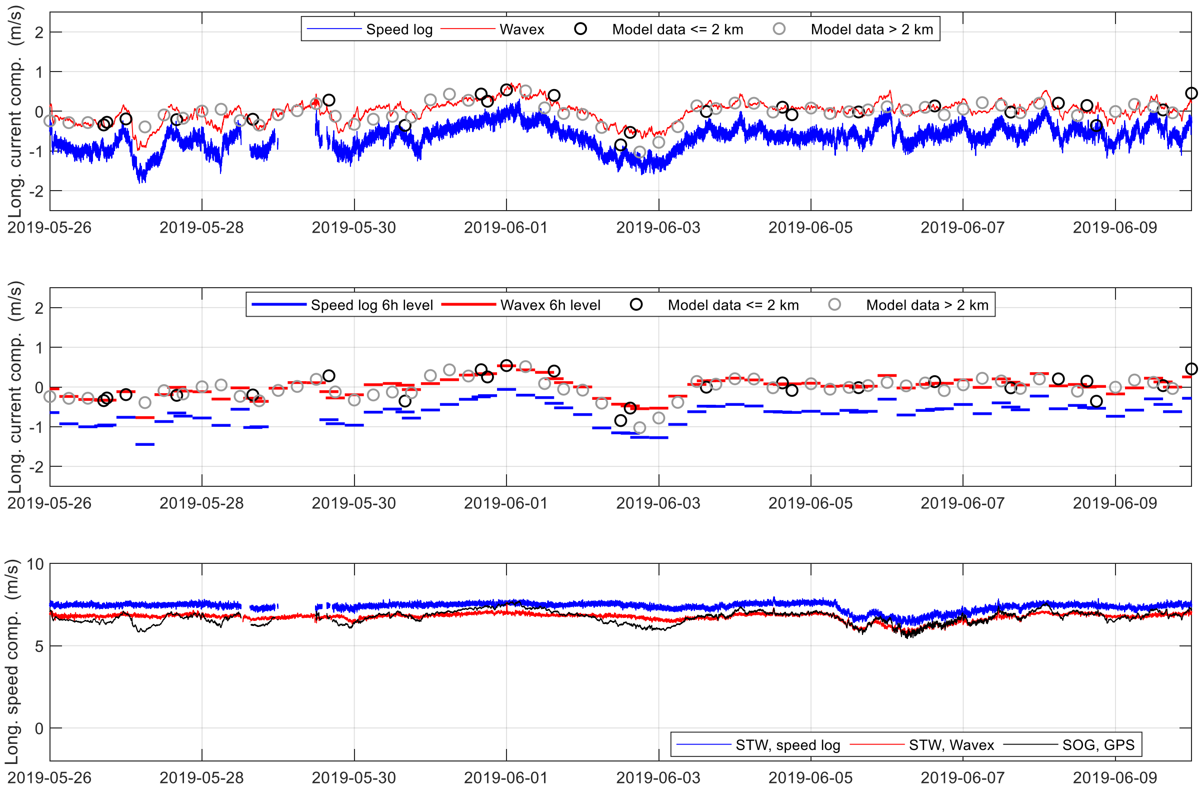


Fig.6: Time series of longitudinal current components and speeds during a voyage around the South American coast (Fig.5).

The data capture during voyage 1 and 2 is complete for both Wavex and speed log. Three hours of data at the end of May 20 (voyage 3) are missing from the Wavex system, in which the system seems to have been turned off. Approximately one day of data around May 16 are missing from the speed log, in addition to one day around June 20. The reason for this is not known. Model data are missing from the voyage report during a longer period from June 14 to June 17. Presumably, this is due to lack of model data for the narrow areas of the Strait of Magellan and for the areas close to the Chilean coast north of the Strait of Magellan (see Fig.5). Except for a period around June 14 due to land and lack of waves in the radar images when BW Rye was passing through a part of the Strait of Magellan, Wavex data have good quality also during voyage 4.

Table I: Correlations, deviations, and Deming regression parameters between longitudinal current components from speed log, Wavex, and model, based on all available data and single voyages

	Voyage	Statistics				Deming regression	
		Corre-lation	RMS deviation (m/s)	Mean deviation (m/s)	Standard deviation (m/s)	Gain	Offset (m/s)
Radar vs speed log	All	0.85	0.47	-0.43	0.18	0.76	0.34
	1	0.97	0.29	-0.25	0.13	0.85	0.20
	2	0.90	0.48	-0.46	0.12	0.91	0.43
	3	0.87	0.48	-0.44	0.19	0.61	0.28
	4	0.84	0.51	-0.48	0.18	0.67	0.33
Radar vs model	All	0.54	0.26	-0.07	0.25	0.79	0.06
Speed log vs model	All	0.48	0.47	0.36	0.31	1.21	-0.35

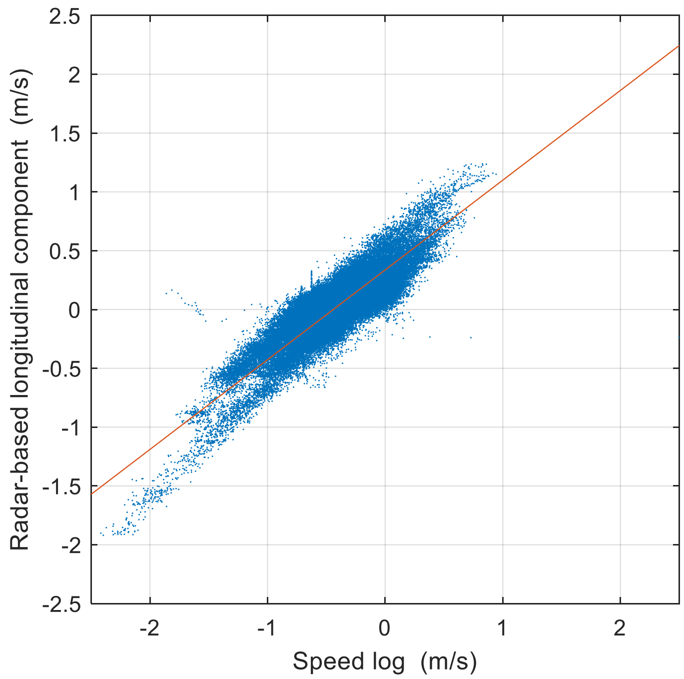


Fig.7: Scatter plot of longitudinal current components from speed log and Wavex, all voyages

3.3. Directional current data

Fig.8 shows wind data and current data from Wavex for the same period, compared with model data. The wind speed varies from 3 to 18 m/s (from 0 to 23 m/s when considering all voyages). Both averaged 6-hour levels and continuous current values from Wavex are shown. An additional centred averaging of 70 minutes is applied to the continuous Wavex data and the wind data, in order to highlight trends and the tidal contribution and to decrease the number of directional wraparounds at low speeds in the visualization. Tidal rotations generated by the tidal current component are often used as indicators of reasonable current measurements. Full clockwise tidal rotations, though somewhat influenced by the vessel's movement and local variations, were observed during several periods, as for instance:

- April 4 – 6 (voyage 1)
- May 18 (voyage 3)
- May 29 – 31 (voyage 4, Fig.8)

In addition, full counterclockwise tidal rotations can be observed during the following periods:

- June 5 – 8 (voyage 4, Fig.8)
- June 9 – 11 (voyage 4)

The reason for the changed direction of rotation is that BW Rye passed the equator around midnight between June 1 and 2; tidal rotations are expected to be clockwise at the northern hemisphere and counterclockwise at the southern hemisphere. This is a very good indicator for reasonable measurements. Also, note how the current direction flattens out for a few days just around equator.

The agreement between model data and measured 6 hours' levels is acceptable for many of the points, for instance when comparing current directions (but not speeds) around equator where the values are relatively stable over large areas. Still, there are also many points for which comparison obviously is less meaningful.

It should be noted that a minor inconsistence occasionally has been observed in the wind speed data when comparing to expected backscatter level in the radar images. In some situations, probably depending on the wind direction, the wind sensor seems to overestimate the wind speed by 1 – 2 m/s during transit when the true wind speed is low. This is probably due to turbulence around the sensor leaving an offset after the vessel motion compensation.

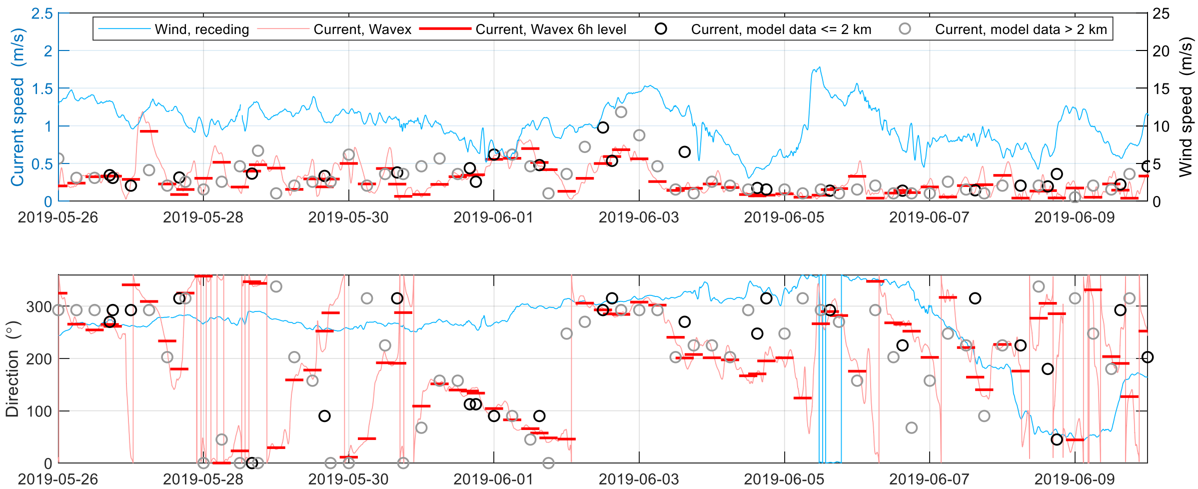


Fig.8: Time series of current and wind data from BW Rye during a voyage around the South American coast (Fig.5), compared to model data. Note how the tidal rotations shift direction from clockwise on the northern hemisphere (May 29-31) to counterclockwise on the southern hemisphere (June 5-8). Equator was crossed approximately at 2019-06-01 22:21.

3.4. Waves

Significant wave heights (H_{m0}) from Wavex for the same period as considered above are shown in Fig.9, together with total wave heights provided by model. Data from the two sources definitively share many of the same trends, and the overall agreement looks reasonable, despite different spatial and temporal premises for the wave height parameters. Statistics are provided in Table II.

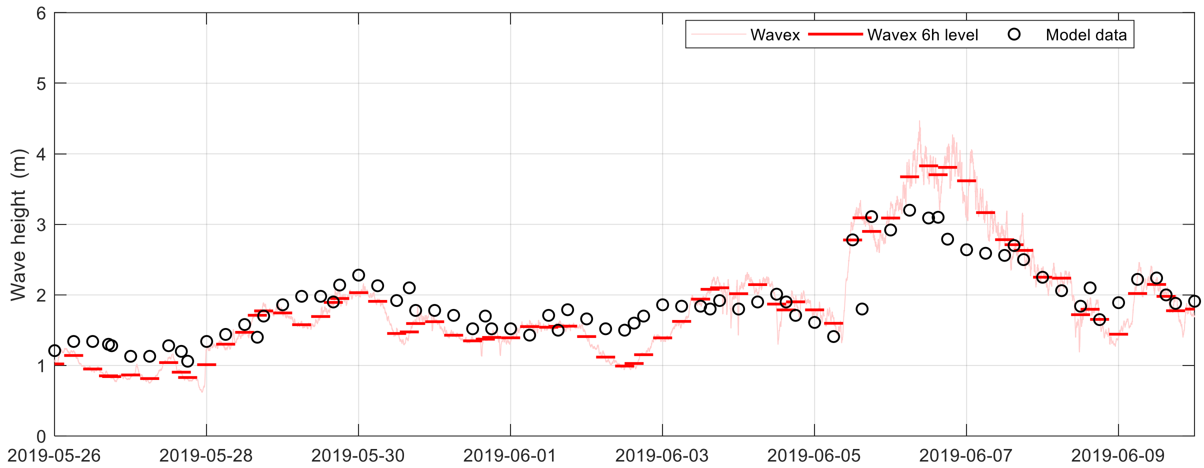


Fig.9: Time series of significant wave heights from BW Rye during a voyage around the South American coast, compared with total wave heights provided by model

Table II: Correlation and deviations between H_{m0} from Wavex and total wave height from model, based on 6 hours levels.

Correlation	RMS deviation	Mean deviation	Standard deviation
0.85	0.47 m	0.17 m	0.44 m

4. Applying onboard measured data as "good weather" decision basis

An important aspect of charterparties is the "good weather" concept, which determines when the contractual claims related to vessel performance are valid. The ship owner or operator provides a performance guarantee specifying a certain fuel consumption that is valid under certain environmental conditions. The conditions are usually specified in terms of wind, wave and current limits. The performance guarantee specifies one or more speed ranges with associated fuel consumption values where the performance guarantee is valid.

Today, good/bad weather assessments are primarily based on model-based data from weather providers and manual observations of weather reported in vessel logbooks. As indicated above and in *Prytz et al. (2019)*, models have significant limitations in providing accurate weather data for a ship at a specific position and time.

Manually assessing the weather is associated with significant uncertainties. Strict and quite time-consuming observation procedures need to be followed to reduce inaccuracies and different kinds of observer bias. Furthermore, the quality of individual observations is questionable, *Tucker et al. (2001)*. Visually observed wave periods are significantly less reliable than instrumentally observed ones, as the eye tends to concentrate on the nearer and steeper short-period waves, thereby ignoring the longer-period and more gently sloping waves, even though the latter may be of greater height and energy, *WMO (1998)*.

In 2017, a vessel performance dispute was considered by the London Court of International Arbitration, *Sigafoose (2017)*, where "good weather" was an important part of the dispute. Among many interesting aspects considered was "evidence of weather". The Court had relative freedom to decide how much evidential weight to attribute to the logs and the reports. Following what they considered was an established view, the Court found that the vessel's logs were generally the best evidence of the conditions experienced. This view could be rebutted with evidence of falsification or exaggeration – but no such evidence was found in this case.

Another aspect of the dispute was the use of the Douglas scale, *Mazarakis (2019),* and differing between sea state, swell and wind sea. With a full directional wave spectrum measured at a vessel's position, a full characterization of the sea state would be available, reducing uncertainty about what conditions a vessel is sailing in, in a time period where its performance is questioned.

The charterer's weather routing report not only sought to exclude periods of adverse current from their performance calculations but went a step further by deducting 0.04 knots from the vessel's speed on the account of an average 0.04 knot boost from following currents, *SOUTHEY (2019)*. The Court concluded that this approach was inappropriate. The reference to 'no adverse current' in the good weather description was intended to ensure the vessel was not affected by current when calculating the performance. To deduct positive current as the weather routing report had sought to do, was considered unacceptable.

Utilizing accurate current data would enable the accurate quantification of the impact of the current on vessel performance, and not only categorize whether there is (adverse) current or not. The Wavex solution measures waves, current and Speed Through Water, and calculates and logs wind data based on input from standard wind sensors. Using accurate onboard-measured data would substantially reduce uncertainty in discussions regarding vessel performance deviations due to:

- Improved weather assessment as the weather affecting the ship at its position at a specific time would be measured accurately.
- Utilizing stable, high-accuracy Speed Through Water measurements would reduce uncertainty in the speed data used for evaluating the charterparty speed-consumption data.

5. Conclusion

The Wavex solution measuring waves, current and STW on BW Rye has been tested and examined. We have observed convincing agreement between Wavex and the speed log when it comes to trends and covariation. However, data from the speed log were influenced by varying offsets, and they were significantly noisier than data from Wavex. The calculated correlation coefficients and standard deviations for the longitudinal current component were in the range 0.84 – 0.97 and in the range 0.12 – 0.19 m/s, respectively. Clockwise (northern hemisphere) and counterclockwise (southern hemisphere) tidal rotations are observed in data from Wavex during the voyages.

Model data comply well with Wavex during some periods with stable currents, when time and position are less important. Beyond that, model data show only a moderate correlation of approximately 0.5 with measured data from Wavex and speed log. A major part of the model data refers to positions too far away from BW Rye to be used for validation of unaveraged data. It should be kept in mind that such models typically provide rough overviews of environmental data on a larger scale in space and time, whereas measurements can provide representative data for local areas of interest, in real-time or as average values, with a higher accuracy than model data. Furthermore, measurements are required as input to models to get reasonable output from models.

An important aspect of charterparties is the "good weather day" concept, which determines when the contractual claims related to vessel performance are valid. Accurate and reliable data for STW, waves and wind for the location of the vessel are of vital importance in order to determine whether the environmental conditions can be categorized as "good weather day" or "bad weather day". It has been shown that the Wavex solution is able to provide high quality data that can be used when analyzing charterparty performance.

References

ANTOLA, M.; SOLONEN, A.; PYÖRRE, J. (2017), *Notorious speed through water*, 2nd HullPIC, Ulrichshusen, pp.156-165

BAUR, M. (2016), *Acquisition and integration of meaningful performance data on board - challenges and experiences*, 1st HullPIC, Pavone, pp.230-238

BOS, M. (2016), *How MetOcean data can improve accuracy and reliability of vessel performance estimates*, 1st HullPIC, Pavone, pp.106-114

BROWN, J.; COLLING, A.; PARK, D.; PHILIPS, J.; ROTHERY, D.; WRIGHT, J. (2001), *Ocean Circulation*, The Open University, Milton Keynes (130 pages)

CARCHEN, A.; PAZOUKI, K.; ATLAR, M. (2017), *Development of an online ship performance monitoring system dedicated for biofouling and anti-fouling coating analysis*, 2nd HullPIC, Ulrichshusen, pp.90-101

FLAGG, C. N.; SCHWARTZE, G.; GOTTLIEB, E.; ROSSBY, T. (1998), *Operating an acoustic Doppler current profiler aboard a container vessel*, J. Atmospheric and Oceanic Techn. 15, pp.257-271

FRITZ, F. (2016), *Practical experiences with vessel performance management and hull condition monitoring*, 1st HullPIC, Pavone, pp.128-136

GANGESKAR, R. (2017), *Automatically calibrated wave spectra by the Miros Wavex system – Accuracy verified*, Miros AS, Asker

GANGESKAR, R.; PRYTZ, G.; SVANES BERTELSEN, V. (2018), *On-Board Real-Time Wave & Current Measurements for Decision Support*, 3rd HullPIC, Redworth, pp.223-233

GANGESKAR, R. (2018a), *Verifying High-Accuracy Ocean Surface Current Measurements by X-Band Radar for Fixed and Moving Installations*, IEEE Trans. Geosci. Remote Sens. 56/8, pp.4845-4855

GANGESKAR, R. (2018b), *Ocean Surface Current Measurement by the Miros Wavex System*, Miros AS, Asker

GANGESKAR, R. (2018c), *Surface Current Measurements from Moving Vessels by Wavex – Verified*, Miros AS, Asker

GANGESKAR, R. (2019), *Measuring the speed through water by Wavex®*, Miros AS, Asker

GOLER, H.; BOSKURT, K. (2017), Speed loss analysis of high-speed ro-ro vessels coated with new antifouling technologies, 2nd HullPIC, Ulrichshusen, pp.173-193

KELLING, J. (2017), *Ultrasound-based antifouling solutions*, 2nd HullPIC, Ulrichshusen, pp.43-49

KING, B. A.; COOPER, E. B. (1993), *Comparison of ship's heading determined from an array of GPS antennas with heading from conventional gyrocompass measurements*, Deep Sea Research Part I: Oceanographic Research Papers 40/11-12, pp.2207-2216

MAZARAKIS, N. (2019), *Why Douglas Sea State 3 Should be Eliminated from Good Weather Clauses*, Stormgeo, https://www.stormgeo.com/solutions/shipping/ship-routing/articles/why-douglas-sea-state-3-should-be-eliminated-from-good-weather-clauses/

NEW, A.L. (1992), *Factors affecting the quality of shipboard acoustic Doppler current profiler data*, Deep Sea Research Part A: Oceanographic Research Papers 39/11-12, pp.1985-1996

POND, S.; PICKARD, G. L. (1983), *Introductory Dynamical Oceanography*, Butterworth-Heinemann, pp.207-219

PRYTZ, G.; GANGESKAR, R.; SVANES BERTELSEN, V. (2019), *Distributing Real-Time Measurements of Speed Through Water from Ship to Shore*, 4th HullPIC, Gubbio, pp.114-127

SIGAFOOSE, J. (2017), Douglas Sea State 3 – London Arbitration Award, Stormgeo, https://www.stormgeo.com/solutions/shipping/fleet-performance/articles/douglas-sea-state-3-london-arbitration-award/

SKOLNIK, M.I. (1980), *Introduction to radar systems*, McGraw-Hill, pp.474-482

SOUTHEY, D (2019), *What is Good Weather?*, https://www.steamshipmutual.com/publications/Articles/what-is-good-weather052019.htm

TUCKER, M.J.; PITT, E.G. (2001), *Waves In Ocean Engineering*, Elsevier, pp.138-139

WMO (1998), *Guide To Wave Analysis And Forecasting*, 2nd ed., WMO-No. 702, pp.89-91

YOUNG, I.R.; ROSENTHAL, W.; ZIEMER, F. (1985), *A three-dimensional analysis of marine radar images for the determination of ocean wave directionality and surface currents*, J. Geophys. Res. 90/C1, pp.1049–1059

Quantifying the Barnacle Fouling Problem on the Global Shipping Fleet

Markus Hoffmann, Catherine Austin, I-Tech AB, Mölndal/Sweden, markus.hoffmann@i-tech.se

Abstract

This paper describes research conducted to quantify the scale of barnacle fouling on the global shipping fleet, both for hull fouling and niche area fouling. Insights into fouling data interpretation for different antifouling system types versus barnacle fouling coverage are presented.

1. Introduction

Ocean going vessels are increasingly at risk from negative commercial impacts associated with marine biofouling accumulation on the hull. Marine fouling is the biological process of single celled organisms, algae and hard-shelled organisms, predominantly barnacles, attaching to submerged surfaces and colonising at a rapid rate.

There are approximately 5000 different fouling species that are found in the world's oceans and these can be classified into micro fouling which comprise slime fouling and macro fouling which comprises weed fouling and animal fouling (hard, with a shell and soft, without a shell).

Any organisms anchored on a ship's hull create increased hydrodynamic drag (commonly referred to as added frictional resistance) which significantly decreases hull performance. Hard (with a shell) animal fouling (noted as calcareous fouling in Table I) which includes molluscs, bryozoans, tubeworms and the most common of all - barnacles, of which around 1000 species are currently known - cause the greatest penalty in terms of hydrodynamic drag when attached to a ship's hull.

A biofouled vessel must use more power, and therefore, burn more fuel to attain the same speed through water when in active service, resulting in higher fuel costs for the ship operator. Alternatively, the vessel will suffer speed losses to maintain a set fuel consumption level. Therefore, the most significant financial impact for the shipping industry is the increase in fuel consumption due to the adverse effect that biofouling on the ship hull has on hydrodynamic performance, as detailed in Table I, or late arrival penalties at port.

Table I: Roughness and fouling penalties - adapted from *Schultz (2007)*

Hull condition	Additional shaft power to sustain speed (%)
Freshly applied coating	0
Deteriorated coating or thin slime	9
Heavy slime	19
Small calcareous fouling or macroalgae	33
Medium calcareous fouling	52
Heavy calcareous fouling	84

A hull suffering from heavy biofouling is also extremely impactful on maintenance costs. Costs associated with hull cleaning services are factored into a ship operator's operating expenditures (OPEX). However, as global biofouling risk increases, hull cleaning is likely to be required more frequently, increasing maintenance costs. Repeated cleaning of the hull can also remove layers of the antifouling coating, reducing its service life.

In addition, growing regulatory focus on the transportation of invasive aquatic species by the international shipping fleet can create a great threat to biodiversity and can also impact a ship commercially. Some regional regulations are already in force that allow ports to refuse entry of heavily bio-fouled ships, resulting in greater financial costs for the operator. On an international level, the

International Maritime Organization (IMO) has recently shifted its focus on tackling invasive aquatic species transfer via ballast water onto hull as a vector for biofouling.

The aforementioned issues are driving the need for high performance, advanced antifouling technology in the maritime industry. Ship operators are increasingly demanding antifouling paints that are both well-suited to specific ship trading patterns, and varying activity levels in addition to protecting against both soft and hard fouling. When looking at the future trading potential, ship operators need to ensure that their ship is protected wherever it sails, whether it be in constant active service, idle for long periods of time, or is at risk of fluctuating between the two.

This future-proofing approach to antifouling coating selection, without any certainty of future trade, is exerting great pressure on the coating suppliers, prospering great innovation and new approaches of biofouling prevention technology using the active agent Selektope®. This is supported by increasing demand for antifouling coatings that contain the unique, anti-barnacle active agent from ship owners and operators.

2. Fouling control technology

Biological fouling control technology is used on the underwater hull area of vessels to prevent the settlement of fouling species. There are essentially two main types of fouling control technology, foul release coatings and biocidal antifouling coatings.

A biocidal antifouling coating comprises a soluble, or partially soluble, resin system that contains a mixture of biocide(s) effective against a broad range of fouling organisms. They are the most widely used technology for fouling control and account for approximately 90% of the fouling control technology market.

These types of antifouling coatings primarily differ by the resin system used, also referred to as ‘delivery mechanism’, and the level and type of biocides used. The solubility of the resin system and the efficacy of the biocides used are the key parameters determining the overall performance of the coating. The two main types of biocidal antifouling resins are: Controlled Depletion Polymers (CDPs) and Self-Polishing Copolymers (SPCs).

Controlled Depletion Polymers coatings utilise a combination of soluble resin (typically rosin, either natural or synthetic) and an insoluble resin. Varying the ratio of soluble to insoluble material allows adjustment of the rate of dissolution and hence the rate of release of biocide. Once in seawater, the soluble resin begins to dissolve leaving a depleted zone (insoluble resin) at the surface called the leach layer. The thickness of the leach layer increases over time slowing the biocide release to a point where it is no longer as effective at preventing fouling. This point is reached typically after approximately three years.

In a Self-Polishing Copolymers coating, the most common binder systems used are based on either copper acrylate, silyl acrylate / silyl methacrylate or zinc acrylate. These resin systems convert from unsoluble to soluble by a via hydrolysis, a chemical reaction with seawater, and dissolve or ‘polish’ in a controlled manner, maintaining a thin leach layer of a constant thickness.

This results in a controlled biocide release rate and a more predictable fouling control performance. Careful selection of the Self-Polishing Copolymers and associated biocide package enables the antifouling coating system to be tailored to the trading requirements of the ship.

3. Use of biocides in antifouling systems

Since the complete prohibition of the use of tri-butyl-tin (TBT) in antifouling coatings by 1 January 2008, as enforced by the IMO, suppliers of marine coatings have faced increasing pressure to offer antifouling coating products that deliver the same level of effectiveness as those that previously contained TBT for preventing the build-up of biofouling on ship wetted hard surfaces.

The banning of TBT use forced the marine coatings sector to reconstruct their formulations to accommodate different biocides, with copper designated as the favoured candidate, supplemented with booster biocides. Soon after, biocides faced new regulatory challenges in the shape of the EU Directive on Biocidal Products (98/8/EC). The effect of this was the number of certified biocides available for use in antifouling coatings reducing in number to just 12 active substances (active agents).

Biocides are used to prevent the attachment of different fouling types (animal, weed and slime) to the underwater hull area. In order to be effective across the entire range of fouling organisms, a combination of biocides is generally used.

Typical biocide packages usually comprise of a blend of an inorganic biocide (usually cuprous oxide) and one or more ‘booster biocides’ (organic and/or organometallic) to be effective across a spectrum of target organisms. Example biocide packages used in antifouling products are as shown in Table II.

Table II: Biocide packages

Number of biocides	Biocide package
Biocide free	Biocide free
Biocide	Copper Pyrithione
	Copper Oxide
Biocides	Copper Oxide / Copper Pyrithione
	Copper Oxide / Seanine 211
	Copper Oxide / Zineb
	Copper Oxide / Zinc Pyrithione
	Zinc Pyrithione / Pyridine-triphenylboron
Biocides	Copper Oxide / Copper Pyrithione / Zineb

4. The development of Selektope® as an alternative biocide

Neither scheduling penalties, nor increased fuel costs were acceptable to a globalised industry reliant on just in time delivery. Since barnacle fouling causes a huge negative impact of fuel consumption and/or speed loss, a solution had to be found. That solution was Selektope®.

In February 2000, biologists at the University of Gothenburg published a research paper on biofouling in Swedish waters. Researchers had been investigating how a range of substances that would prevent the settlement of hard fouling when dissolved in seawater could be used. This research focused on the barnacle Amphibalanus improvisus, and its ‘colonisation’ of man-made surfaces at the larval stage. The goal of the research was to discover ‘adrenoceptor active compounds’ that manipulated the barnacle larvae’s behaviour to inhibit invertebrate larvae from settling. *Dahlström et al*. (2000) found that larval-stage receptors were remarkably responsive to one substance in particular– medetomidine.

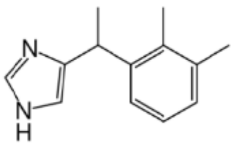
CAS-No. **EINECS-no**	86347-14-0 Not listed
IUPAC Name	4-[1-(2,3-dimethylphenyl)ethyl]-*1H*-imidazole
Other common name	Medetomidine
Molecular formula	$C_{13}H_{16}N_2$
Structural formula	
Molecular weight (g/mol)	200,28 g/mol

Fig.1: Medetomidine identity

In a counter-intuitive discovery, given its sedative effect on vertebrates, medetomidine was found to induce hyperactivity in the barnacle larvae to disrupt the settling process, similar to the effects to a small dose of adrenaline in humans. Therefore, this bioactive substance prevented barnacle larvae attempting to settle on a hard substrate.

Medetomidine was also distinguished by its reversible effects on barnacle cyprid larvae. Any larvae that came into contact with the substance could still later metamorphose into juvenile barnacles with no apparent ill effect.

In collaboration with two Finnish universities, Swedish researchers discovered that medetomidine could bind to a specific group of receptors, the octopamine receptors. The receptors were cloned and the causality between the receptor and medetomidine was established. Further studies led the researchers to link the binding to octopamine receptors to changes in the larval behaviour at a surface. This explained the high efficacy in preventing and deterring barnacle larvae from an antifouling paint without its being toxic to the barnacles.

Fig.2: Cyprid larvae barnacle life stage

Fig.3: Adult stage of the barnacle

During initial panel testing, a further discovery was made. Remarkably, a polymer film containing medetomidine in a concentration equivalent to 0.02% by weight volume rejected 97% of the aggressive Barnacle improvus after two weeks, and 96% after four weeks. No other macro-fouling organisms were present at all. A further distinction pointed towards medetomidine's potential for "large scale synthesis": its "tendency to accumulate at the solid/liquid interface" across the full extent of a surface.

These significant research findings catalysed the development of the industry's first biotechnology biocide. I-Tech AB commercialised the use of medetomidine in marine coatings, owning all intellectual property (IP) and regulatory rights to the antifouling agent under the brand name Selektope®. I-Tech also controls the largest and most efficient source of medetomidine production.

In 2009, buoyed by the further confirmation of earlier research, I-Tech entered a new stage in the development of Selektope®, by initiating the registration of the active agent for regulatory approvals. Few can doubt the dedication required to submit a new substance to the European Union's Biocidal Products Regulation's (BPR) evaluation process; the BPR (EU528/2012) dossier consists of more than 20000 pages 528 files and refers to 90 investigations regarding human and environmental safety. The result was that Selektope® was granted full approval in 2016 for use as a marine biocide. Today, Selektope® is one of only twelve active substances certified as a biocide available for use in antifouling coatings under the EU BPR.

To this day, Selektope® has received approvals in all leading markets for new builds and dry-docking including China, South Korea and Japan. In the EU, Selektope® has been approved for all relevant use-types l. For Africa, South America and the rest of Asia, no registration is needed for the use of Selektope®. Following 15 years of development time and numerous regulatory hurdles, the first commercial antifouling coating product containing Selektope® was applied to the vertical sides of a ship in 2015 with the first commercial product containing Selektope® being officially launched into the market in 2016.

5. The use of Selektope® in Self-Polishing Copolymers coatings

Selektope® has not been used in 'foul release' coatings with low surface energy based on siloxane elastomers and fluoropolymers, yet. Selektope® is a biocide that is currently only used in Self-Polishing Copolymers and Controlled Depletion Polymers coating types. Self-Polishing Copolymers coatings rely on the friction generated by the ship's motion through water causing tiny quantities of the base polymer paint to hydrolyse and to leach at a predetermined rate, while the active antifouling maintains its performance evenly through the paint's lifetime.

Selektope® is a biocide that has highly favourable antifouling properties at low concentrations (nano Molar). To obtain full protection against barnacle fouling, 0.1 - 0.3% w/w of Selektope® should be used in a wet paint formulation. Just 2 grams Selektope® is used per litre of paint, comparable to 500-700 grams of copper oxide used per litre of paint for barnacle prevention.

Selektope® binds to pigment and other particles in the paint system and is therefore, continuously released in the same way as other active substances and components. This contributes to long-term performance for as long as the paint remains on the hull. The paint formulation, which mainly comprises binding agents, biocides, pigment and filler material, is applied to the hull using a traditional spraying method. The compatibility between Selektope® and the paint matrix in the marine coatings industry, ensures as slow and steady release secures the antifouling effect over time.

However, how and when Selektope® is added during the formulation process is key to controlling the release rate of Selektope® from an antifouling paint. To prevent premature depletion of Selektope® the molecule should be able to interact with a carrier in the paint mixture. A carrier could be an inorganic particle such as zinc- or cuprous oxide. It could also be a metal ion such as Zn2+ or Cu2+, or an acid group on a binder, for example the carboxylic acid on rosin.

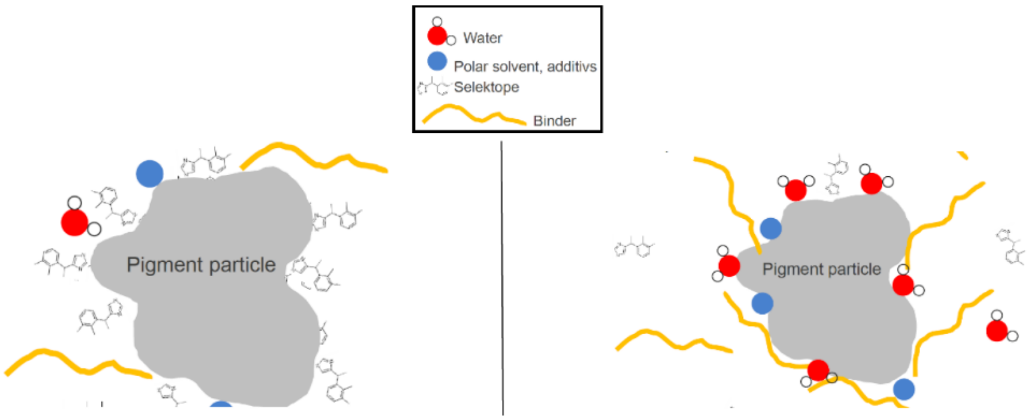


Fig.4: Selektope® added before the binder and other components - good adhesion will occur versus if Selektope® added at the end of the formulation process – weaker or no adhesion occurs potentially leading to premature depletion of Selektope®

Although most Selektope®-containing antifouling paint products on the market are combinations of copper oxides and Selektope®, Chugoku Marine Paints have developed a paint that is copper free. Therefore, the concentration of hard fouling biocides in the paint has been reduced, while other qualities, such as prevention of soft fouling (e.g. slime and seaweed) have been notably improved.

6. Novel research: quantifying the scale of the barnacle fouling problem

In January 2020, I-Tech contracted Safinah Group (Safinah) to provide a report detailing data regarding barnacle fouling obtained from Safinah's attendance at vessel dry dockings.

6.1. Methodology

Safinah's independent analysis of dry dock data and barnacle fouling, detailed many factors. For the purposes of this paper, we will present the following:

i. Number of vessels (including vessel type) that have had barnacle fouling issues.
ii. Reported barnacle coverage (m^2).
iii. Location of barnacle fouling on the vessel.

The fouling control products included in the research were categorised based on publicly available source, including:

a. Material Safety Data Sheets.
b. Technical Data Sheets.
c. Paint suppliers marketing literature.
d. Safinah's extensive internal market knowledge of fouling control technology.

The fouling control products included in this research were:

- Biocidal antifouling:
  i) Low grade: Rosin only resin system, no Self-Polishing Copolymers content.
  ii) Medium grade: Hybrid type containing Self-Polishing Copolymers and > 5% rosin (wt.).
  iii) High grade: Self-Polishing Copolymers type with < 5% rosin (wt.).
- Foul release:
  i) Medium grade: First generation foul release systems.
  ii) High grade: Latest generation foul release and foul release with biocide.

6.2. Data source

The data used in the research was based on Safinah's historical dry dock attendance reports / inspections from 2015 – 2019, a summary of the data set is provided below in Table III.

Table III: Summary of the vessel data from dry dock reports

Number of vessels	Number of observations (dry dock reports)	Number of vessels with single dry dock	Number of vessels with multiple dry docks
249	268	231	17 (2 Dry Docks) 1 (3 dry docks)

6.3. Vessel type split

The 249 vessels were split by type as shown in Table IV.

Table IV: Vessel type

Vessel Type	Number of vessels	Percentage (%) split
Bulk Carrier	28	11
Car Carrier	15	6
Chemical / Product Tanker	78	31
Container	7	3
Crude Oil tanker	38	15
Cruise Ship	21	8
Ferry	1	0.4
LNG	17	7
LPG	33	13
Oil Products Tanker	11	4
Total	**249**	**100**

6.4. Analysis of the data

The overall animal fouling coverage by percentage of the total underwater hull for all vessels on which fouling condition could be assessed on arrival at the dry dock is shown in Fig.5, this is based on a total of 198 vessels.

This data tells us that the majority of vessels surveyed (112 vessels representing 56%) had between 0-10% barnacle fouling coverage on the hull. 30 out of 198 vessels surveyed (15%) had between 10-20% animal fouling coverage on the hull. 19 vessels (representing approx. 10% of all vessels surveyed) had 20-30% animal fouling coverage on the hull. 13 vessels (representing 6% of vessels surveyed) had 30-40% animal fouling coverage on the hull. The remaining 20 vessels surveyed had between 40-80% animal fouling coverage on the hull (representing approx. 10%). Only 1% of vessels surveyed (2 vessels of 198) had animal fouling coverage of 80-100%.

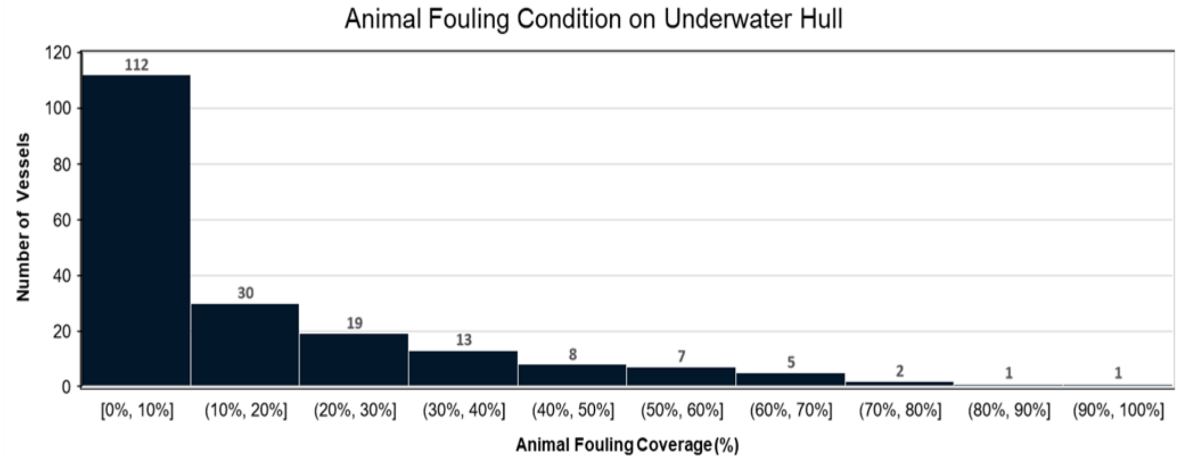


Fig.5: Animal fouling percentage coverage of the underwater hull

The translation of percentage animal fouling coverage of the underwater hull into actual hull surface area covered fouled by barnacles plotted as an actual m^2 coverage across the underwater hull area is presented in Fig.6.

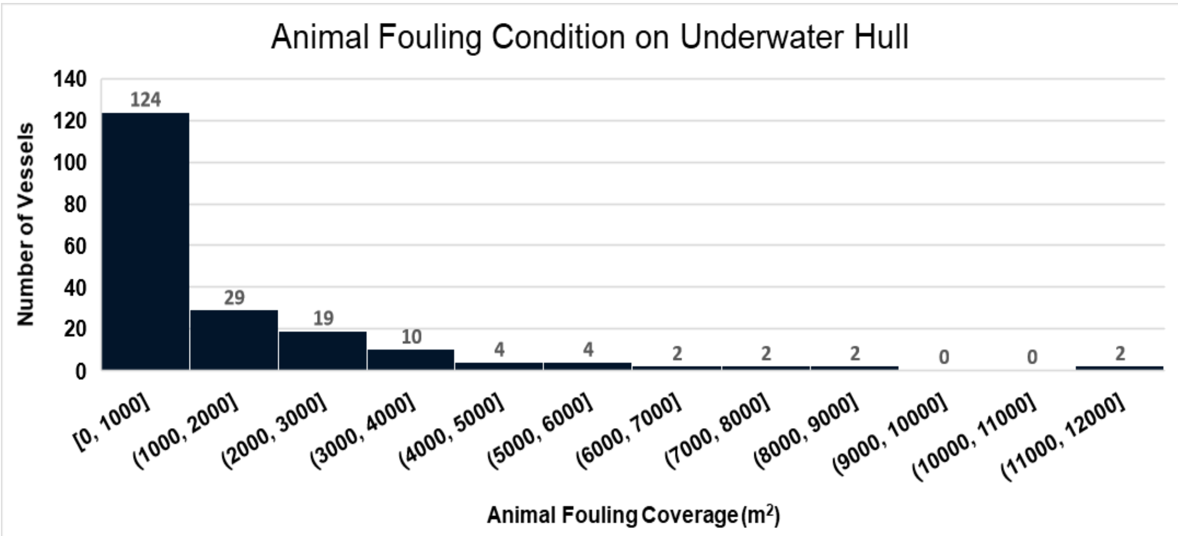


Fig.6: Animal fouling coverage of underwater hull as m^2

The data shows that

- 124 vessels out of 198 (62%) had underwater hull animal fouling coverage of up to $1000m^2$

- 29 vessels out of 198 (~15%) had underwater hull animal fouling coverage of up to 2000m^2
- 19 vessels out of 198 (~10%) had underwater hull animal fouling coverage of up to 3000m^2
- 10 vessels out of 198 (~5%) had underwater hull animal fouling coverage of up to 4000m^2
- 14 vessels had substantial underwater hull animal fouling coverage between 4000m^2 – 9000m^2.
- Only 2 vessels surveyed had significant underwater hull animal fouling coverage between 11000-12000m^2.

In Fig.7, the vessels in the 0 – 1000m^2 segment from Fig.6 have been split out further into 100m^2 segments. This shows us that 47% of vessels surveyed (58 of 123) had 0-100m^2 of animal fouling coverage. The other 53% of vessels have animal fouling of at least 100m^2 or more. 100-200m^2 coverage (13 vessels) and 600m^2 – 700m^2 coverage (13 vessels) represent the second largest group of vessels surveyed (20%). 9% of vessels surveyed had animal fouling coverage between 700-800m^2 and 6% of vessels surveyed had animal fouling coverage between 400-500m^2.

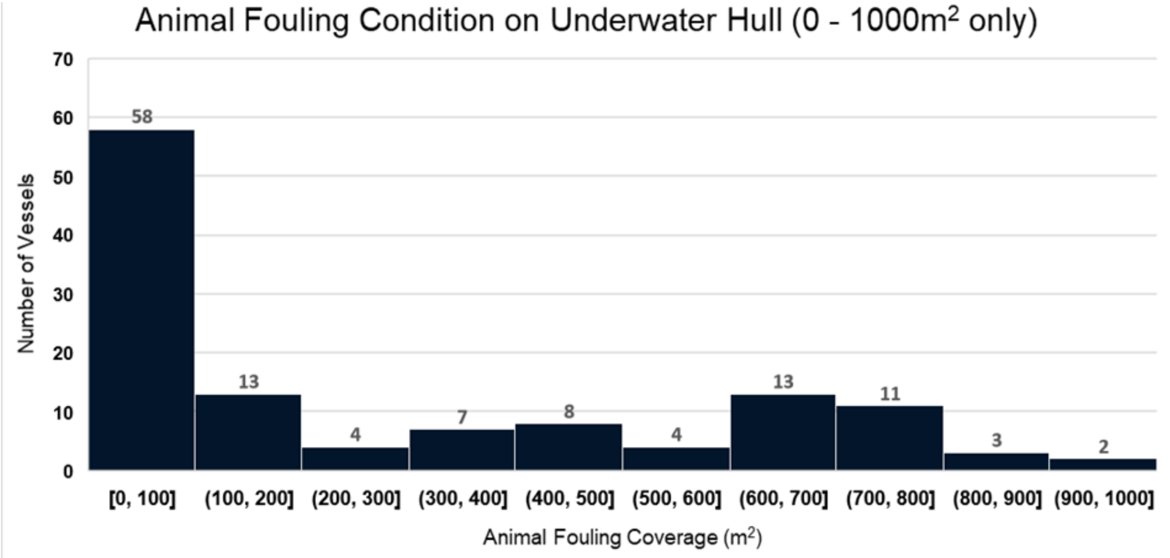


Fig.7: Animal fouling coverage of underwater hull as m^2(0 – 1000m^2 only)

6.5. Analysis by fouling type

572 observations of fouling condition were observed at drydock, split by area vertical sides (VS), flat bottom (FB), boottop (BT) and Seachest. The results are presented in Fig.8.

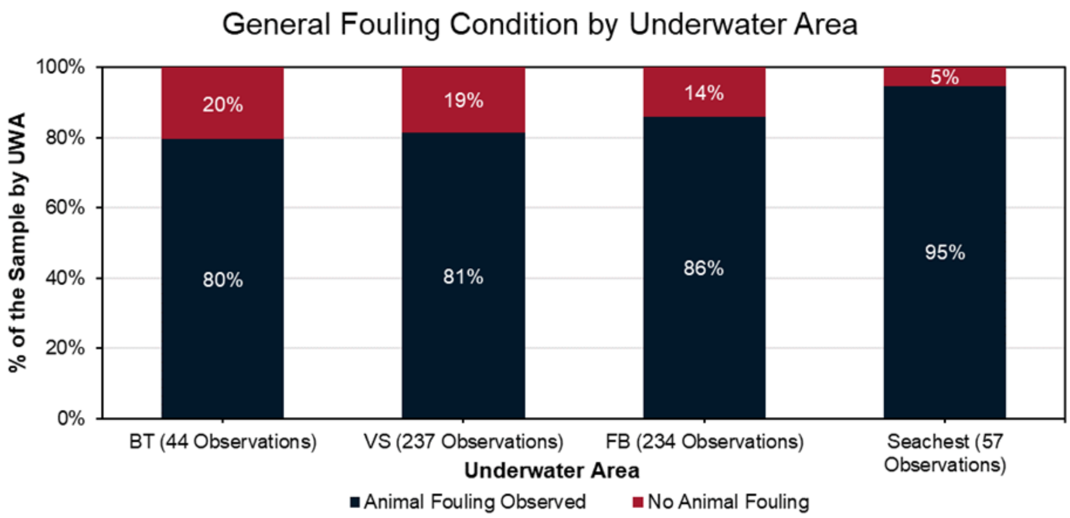


Fig.8: Fouling type from all observations

Whilst animal fouling is present on the majority of the observations for all locations, this is particularly the case for the flat bottom and seachest. Since these areas receive little or no ultraviolet (UV) light which is not required for animal fouling, unlike weed fouling, this result comes as no surprise.

This data was further quantified, in Fig.9, to understand the combinations of fouling types observed. As expected, animal fouling only (~74% of observations) dominates in sea chests. This data shows that the dominant fouling combination for bootop, vertical sides and flat bottom does include animal fouling since a mixture of barnacle fouling, weed and slime was the most encountered fouling condition logged for the vessels surveyed.

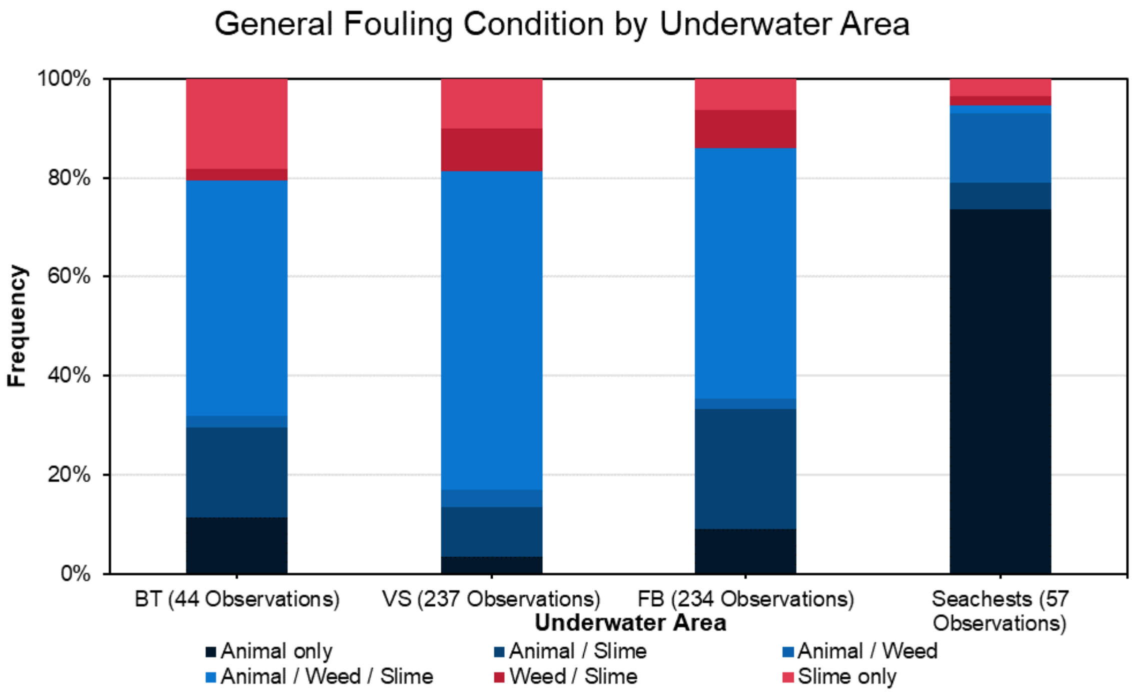


Fig.9: Combinations of fouling type from all observations

6.6. Fouling type by relative vessel activity

A further split of the data was made by the relative activity of the vessel types, as shown in Table V.

Table V: Relative vessel activity

Relatively lower activity	Relatively higher activity
Chemical / Product Tanker	Car Carrier
Crude Oil Tanker (up to 80k DWT)	Crude Oil Tanker (up to >80k DWT)
LPG	Container
Oil Products Tanker	Cruise Ship
	Ferry
	LNG

Whilst the actual activities of the vessel in the dataset were unknown, the vessel grouped by relative vessel activity are typical industry assumptions. The fouling condition for the lower and higher activity vessels are presented in Figs.10 and 11.

As expected, the frequency of animal fouling occuring increases on the lower activity vessels and for all vessels is generally higher on the FB and sea chest areas. Further analysis can then be undertaken to just take into account animal fouling coverage by releative vessel activity, see Fig.12. Animal fouling coverage increases for relatively lower activity vessels with 45% of observations with animal fouling coverage > 10% compared to 27% for relatively higher activity vessels.

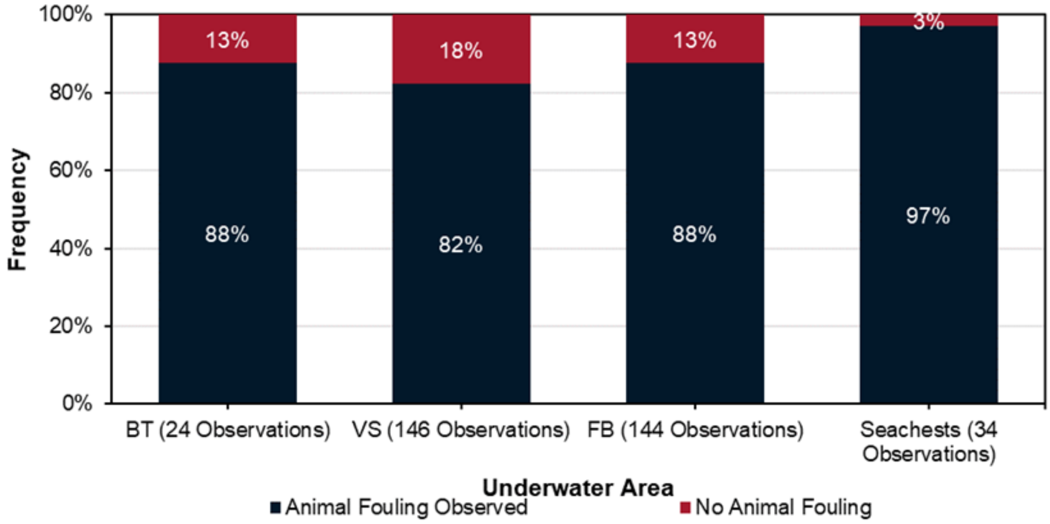


Fig.10: Fouling condition for relatively lower activity vessels

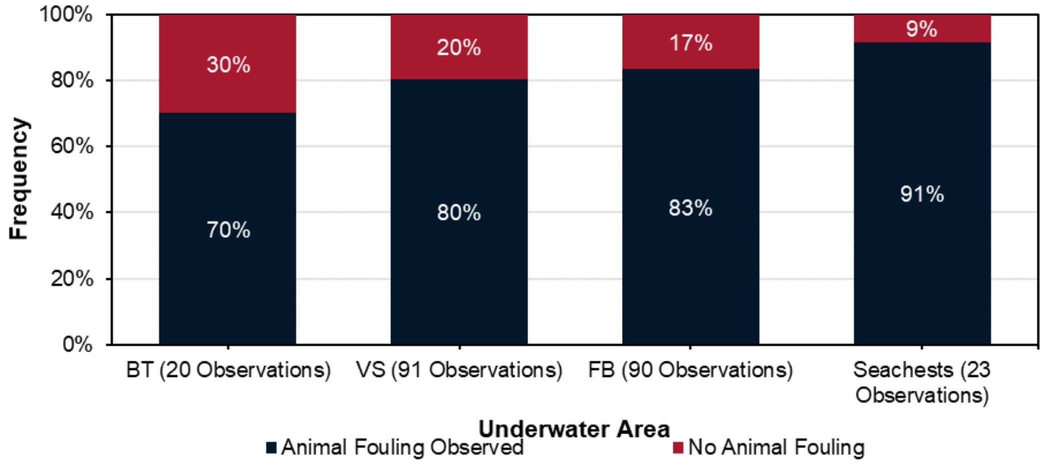


Fig.11: Fouling condition for relatively higher activity vessels

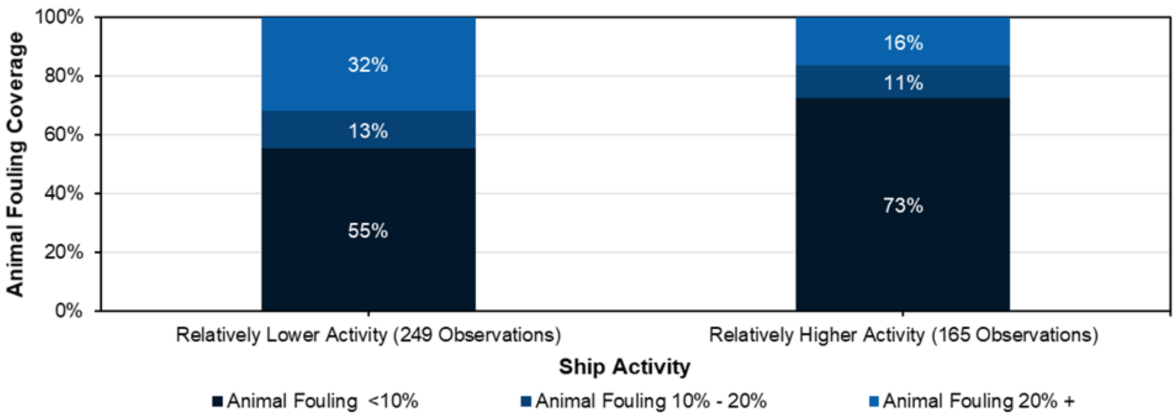


Fig.12: Animal fouling coverage by relative vessel activity

6.7. Animal fouling by underwater area

In terms of animal fouling, this can be split by underwater area location e.g. bootop (BT), vertical sides (VS) and flat bottom (FB), see Fig.13. The data reveals that animal fouling coverage is significantly greater across the flat bottom (FB) compared to the vertical sides (VS) and bootop (BT), which is expected.

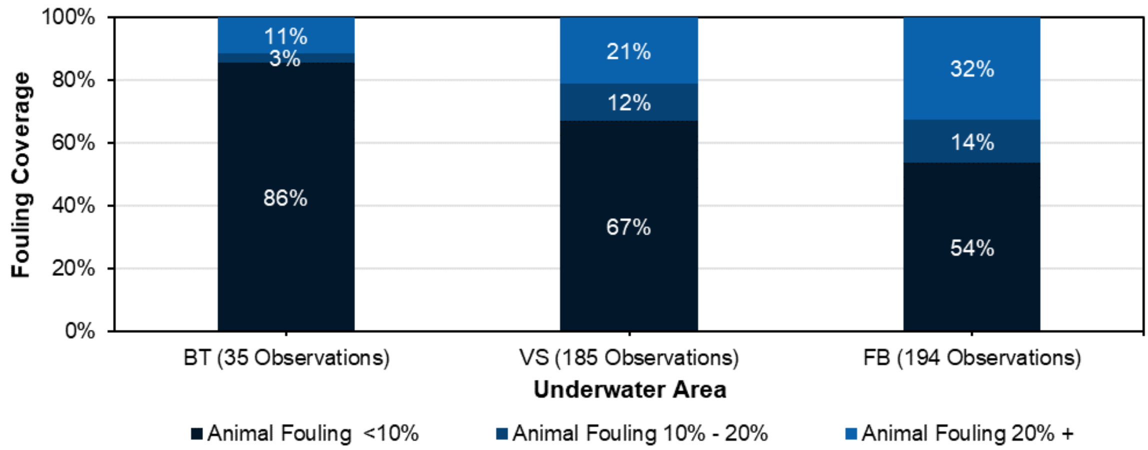


Fig.13: Animal fouling coverage by location

6.8. Novel research summary (prepared by Safinah Group)

Based on a data set of 249 vessels with a total of 268 dry dockings it has been observed that animal (barnacle) fouling is clearly a problem. Approximately 30% of all vessels with animal fouling have barnacle coverage >20% of the total underwater hull area. Heavy animal fouling will impart an increase in vessel drag up to and in excess of 50% which equates to a significant increase in the fuel consumption and emissions. Whilst the higher performance products show improved resistance to barnacle fouling there is still significant evidence of barnacle fouling on these products. Barnacle fouling as expected is more predominant on the flat bottom and sea chests when compared to the other main underwater area, the vertical sides.

The evidence from the drydocking data set clearly points to a need for further improvement of the current fouling control range in resisting animal fouling. Furthermore, the dry dock reports do not provide details as to a vessel's activity and/or static periods. Extended static periods are known to be particularly challenging to both biocidal and foul release coatings types. Independent data showing antifouling coatings pigmented with Selektope® delivering improved and longer fouling protection during extended static periods would be a real benefit to ship operators.

7. Conclusion

Selektope® is currently being used on over 400 vessels and I-Tech anticipate this number growing significantly in the near future. Independent data analysis of added resistance on the ship hull, dive inspections and static panel tests confirmed, and continue to confirm, the barnacle repellent power of this biotechnology when used in marine antifouling coatings. The properties of Selektope also enable new ways of formulation to increase also the performance of other biocides against algae and slime. I-Tech intends to continue looking for new materials where Selektope® can be incorporated as well as enabling the use of the biotechnology in all currently used antifouling solutions on the market today and in the future.

Biocidal antifouling coatings are generally effective against a wide range of fouling organisms; however current antifouling coating products would benefit from improved antifouling performance over extended static periods, which Selektope® can provide.

Acknowledgement

We thank the University of Gothenburg and the Safinah Group.

References

DAHLSTRÖM, M.; MÅRTENSSON, L.; JONSSON, P.; ARNEBRANT, T.; ELWING, H. (2000), *Surface active adrenoceptor compounds prevent the settlement of cyprid larvae of Balanus improvises,* J. Bioadhesion and Biofilm Research 16, pp.191-203

SCHULTZ, M.P. (2007), *Effects of coating roughness and biofouling on ship resistance and powering,* Biofouling 23, pp.331-341

Dynamic Biofouling Protection

Jan Kelling, **Xavier Mayorga**, HASYTEC Electronics GmbH, Schönkirchen/Germany,
j.kelling@hasytec.com

Abstract

Future biocide-free biofouling management solutions are evolving rapidly. For internal systems and niche areas, ultrasonic systems have proven to be an attractive option in this context. The paper describes the basic approach of the Dynamic Biofouling Protection system and illustrates its effectiveness for various applications with case studies from different vessel.

1. Introduction

Fouling develops in stages, where the initial stage is a microscopic fouling, which collectively may form a biofilm visible to the human eye, Fig.1. See *Kelling (2017a,2018)* for a more extensive discussion. If the biofilm formation is inhibited, the subsequent stages of macrofouling will not develop. Much of the focus of recent research and development into biofouling management have been focused – rightfully and logically – then on inhibiting biofilm formation and development.

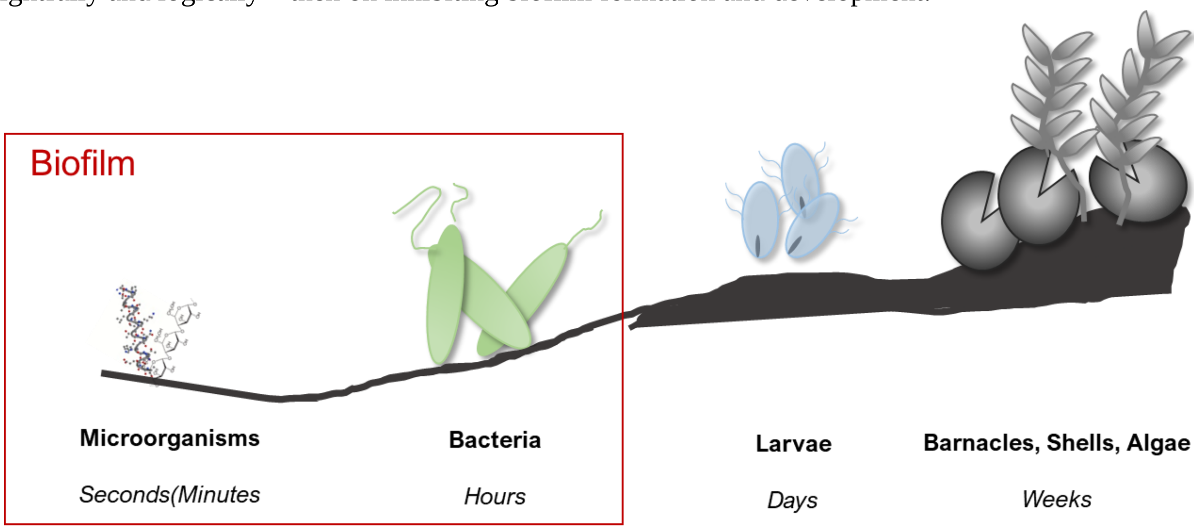


Fig.1: Biofilm as the initial step of marine growth

The classical approach to combat biofouling on ships has been using biocide-containing paints, *Bertram and Yebra (2017)*. In relation to the IMO convention "International Convention on the control of harmful Anti-Fouling Systems on Ships (2001)", the European Union finalized the EU Regulation No. 528/2012. This regulation on biocide containing products regulates the marketing and use of biocide containing products, which due to the activity of the active ingredients contained in them for the protection of humans, animals, materials or products against harmful organisms such as pests or bacteria, may be used. The aim of the regulation is to ensure a better functioning of the biocide containing products market in the EU, while ensuring a high level of protection for human health and for the environment. As an example, almost no copper based active substance will get permission to be used in the future. Every system must be approved to be marketed and the environmentally harmful systems shall be sorted out. This leaves essentially two options:

- taking the risk of using less effective antifouling systems which leads to higher costs for maintenance and repair as well as to higher fuel expenses
- looking for alternatives to replace the currently used antifouling systems

While robotic cleaning solutions are often a cost-effective solution for large, smooth areas, niche areas are unsuited for robotic cleaning. However, niche areas are particularly critical in terms of biofouling and the threat of aquatic invasive species. This is explicitly addressed in IMO's biofouling management guideline. Niche areas are also the focus of inspections of authorities already enforcing biofouling management policies, such as Australia, New Zealand, California and Hawaii State. A complementary solution is needed, and the Dynamic Biofilm Protection (DBP) based on ultrasound is the perfect match for the requirements of IMO's biofouling guideline. It will be described in the following.

2. Dynamic Biofilm Protection

Using low-powered ultrasound (which does not cause cavitation in a certain combination of frequencies, altitudes and power consumption) avoids biofilm formation on any liquid carrying surface, *Kelling (2017b)*. This working principle is still relatively unknown in the shipping industry, but it has large potential and enjoys a rapidly growing customer base.

The Dynamic Biofilm Protection based on ultrasonic protection against biofouling may be used for external spaces, such as pipes, heat exchangers, sea chests, or tanks, Fig.2. But they may also be used for hull protection. For smaller vessels, the complete hull may be protected, but for large cargo vessels, the typical applications focus on niche areas, such as side thrusters, sea chests, etc.

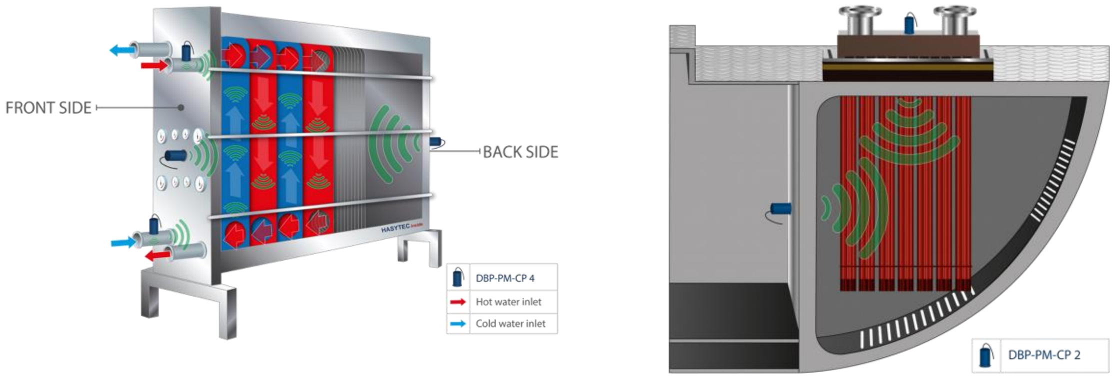


Fig.2: Internal biofouling protection using DBP. Small blue cylinders are 'transducers'

The ultrasonic vibrations are brought into the water via 'transducers', Fig.3, which are attached to the steel hull on the inside, e.g. in the engine room where electrical supply to the transducers is easy. Transducers are relatively low-powered, e.g. 12 W per transducer for average output, 20 W per transducer for maximum output.

Fig.3: Examples of installed transducers

Figs.4 to 7 show results from sample installations, demonstrating the effective protection against biofouling. More such results from shipping industry applications are found in *Kelling (2017a,b)*.

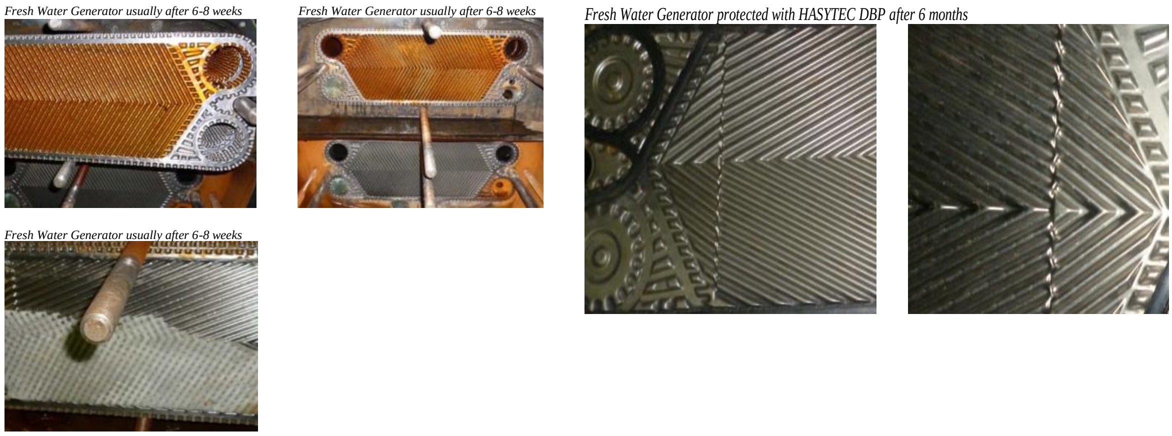


Fig.4: Fresh-water generator after 6-8 weeks without DBP / after 6 months with DBP

Fig.5: Sea Chest view from outside after 3.5 years in operation with DBP

Fig.6: Propeller after 6 months without DBP and comparable propeller after 3 years with DBP

Fig.7: Side thruster before (left) and after (right) installing DBP

3. Summary

Ultrasonic biofouling management continues to gain traction in the maritime industry. We have more then 4500 transducers installed, on a total of more than 230 ships. In a nutshell, the Dynamic Biofouling Protection system is summarized as follows:

- environmentally friendly and sustainable
- maintenance free
- reducing OPEX
- increasing lifetime of vessel`s components & operational safety
- design following shipping industry standards and IP 68 approved

Acknowledgements

HASYTEC electronics GmbH has enjoyed great support from customers and media which have accompanied us from the beginnings of a small start-up to where we are now: the technology leader in maritime ultrasonic biofouling protection. We are grateful for the many awards bestowed upon us: Environmental Performance Award (2017), Hansa Maritime Innovator Award (2017), PitchBlue Jury and Audience Awards (2018), Ocean of Opportunities Award (2018), SEATRADE Engineering Award (2019), and Deutscher Innovationspreis (2020). Thank you.

References

BERTRAM, V.; YEBRA, D.M. (2017), *Past, Present and Prospects of Maritime Antifouling*, 11^{th} HIPER Conf., Zevenwacht, pp.32-43, http://data.hiper-conf.info/Hiper2017_Zevenwacht.pdf

KELLING, J. (2017a), *Ultrasound-based antifouling solutions*, 2^{nd} HullPIC, Ulrichshusen, pp.43-49, http://data.hullpic.info/hullpic2017_ulrichshusen.pdf

KELLING, J. (2017b), *Ultrasonic Technology for Biocide-Free Antifouling*, 11^{th} HIPER Conf., Zevenwacht, pp.70-76, http://data.hiper-conf.info/Hiper2017_Zevenwacht.pdf

KELLING, J. (2018), *Ultrasound – The Silent Revolution in Antifouling*, 3^{rd} HullPIC Conf., Redworth, pp.346-353, http://data.hullpic.info/hullpic2018_redworth.pdf

Fusion of High-Frequency Navigational Data and Noon-Reported Data to Predict Hull Condition

Daniel Schmode, Wärtsilä Voyage, Hamburg/Germany, daniel.schmode@wartsila.com
Matti Antola, Wärtsilä Voyage, Helsinki/Finland, matti.antola@wartsila.com

Abstract

Today's hull performance prediction methods are either based on a) high-frequency sensor-based data logging systems, which are expensive and non-standardized, or on b) low-frequency noon-report data, which are limited in accuracy (among other reasons) because speed and weather are varying in reporting intervals. Here we verify a method that is combining high-frequency data available through standardized navigation equipment (ECDIS) and noon-reporting data. By blending the data together with third-party sources and applying modern machine learning technologies we achieve data quality similar to a) with low investment and operational cost comparable with b). This data is used to monitor hull performance trends.

1. Introduction

Hull performance prediction suffers from various error sources such as measuring errors, modelling errors, implementation errors and statistical errors. The nature of errors can be noise or bias. While noise cancels out when enough data points are aggregated, bias requires corrective action, *Schmode (2017)*. Here we address a bias-type error which is introduced by aggregating varying variables (speed, consumption, and weather) over too long (~24h) periods. We refer to this as 'aggregation error' in the following. While other industries can afford full-scale model test e.g. in wind tunnels, quantifying model errors on vessel data is nearly impossible because a) the current vessel conditions are unknown b) environmental influences cannot be eliminated.

In the following we present a purely numerical experiment that quantifies the aggregation error for typical vessel operation. We will then apply a method to eliminate the aggregation error and discuss the results. Finally, we will investigate the robustness of this method with regards to input errors.

2. Quantifying the aggregation error

Here we are interested in an error introduced by statistical processing. Therefore, we use a simple digital twin. For simplicity, we assume good weather and neglect added resistance for now. We also assume engine specific fuel oil consumption to be constant. The digital twin's consumption is defined as

$$F_v(S, D) = a + (b + cD)\, S^3$$

F_v is the fuel flow rate. Subscript v indicates a virtual (taken from digital twin) value. S is speed through water, D draft. a, b and c are the models constants which we keep constant.

The same investigation can be carried out for a model of propulsion power. This would eliminate the effect of engine performance. In our experience, many vessels do not have a torque meter or if they have one it cannot integrate the propulsion power and the crew is reporting an instantaneous power at noon. In such cases, measuring propulsion power is even less accurate then measuring fuel over a noon period (which is a proper integration in time).

Fig.1 displays a realistic speed profile over ~7 weeks. Various speed changes and stoppages are visible. The noon periods are indicated. On a vessel without auto-logging equipment the crew will read the fuel consumption, distance and weather condition at the end of each noon period. Speed is assumed to be distance/duration. For variables with linear relation this aggregation is correct. Speed and power have at least a cubic relation. For non-uniform v, we have

$$\bar{v}^3 \neq \overline{v^3}$$

Thus, such an aggregation causes an error.

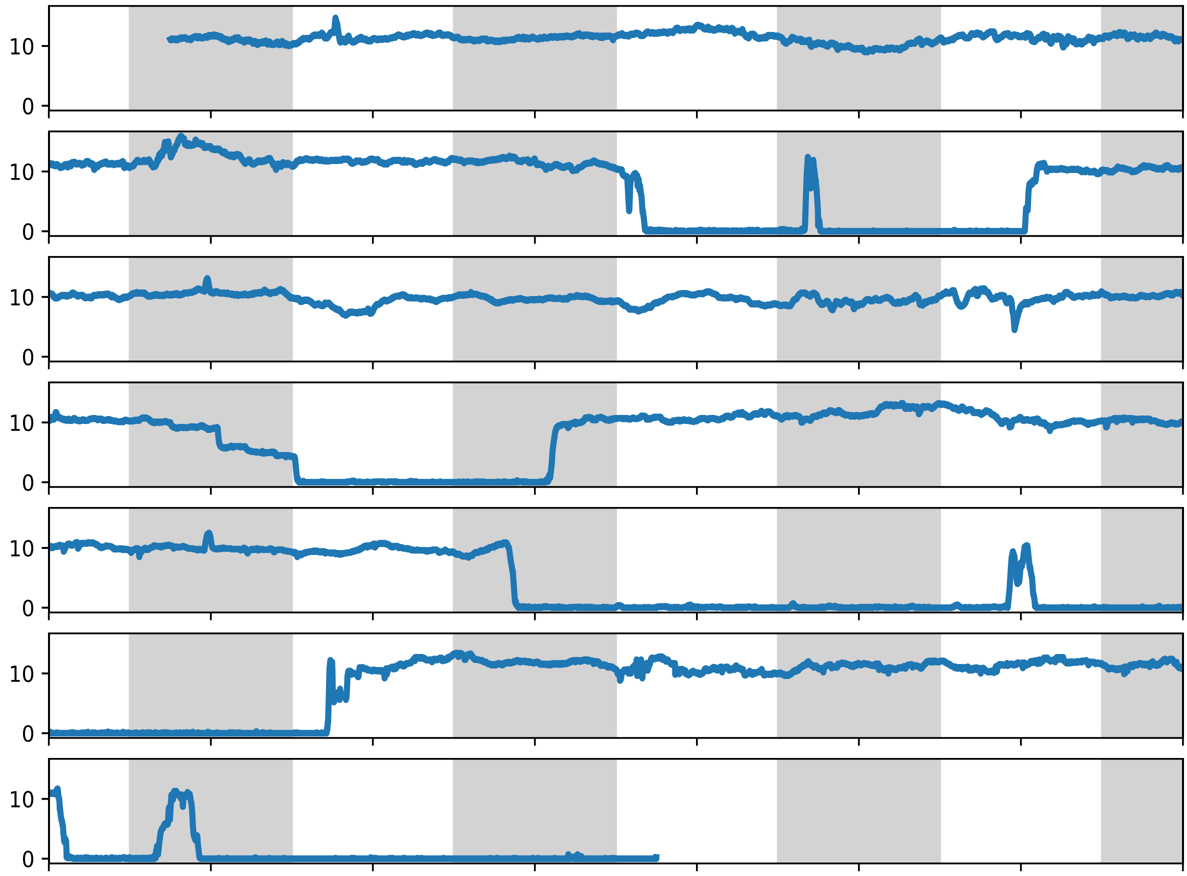


Fig.1: Typical speed profile over time with noon periods marked

To quantify this aggregation error, we apply the digital twin to this speed profile from Fig.**1** assuming the draft constant. Fig.2 shows the speed consumption for a noon period with low variation in speed. Fig.2 (left) shows timelines for speed and consumption predicted by the digital twin. Blue dots mark the high-frequency data. Average and standard deviation are plotted as green lines. The speed-consumption graph is given in Fig.2 (right bottom), plotting speed and aggregated consumption in green. The bars indicate the standard deviation. The aggregated point is close to the curve defined by the high-frequency data. Fig.3 illustrates the same relation for a noon period with high variation. Here the aggregated consumption lies significantly above the high-frequency data points. This difference is caused by the aggregation error described above.

3. Eliminating Aggregation error

In all noon-to-noon reporting scenarios with varying speed/rpm or weather condition, this aggregation error is present. Its magnitude depends on the variance in reported variables. The aggregation error can be reduced by more frequent reporting.

Auto-logging the fuel meters and speed is one option. Retrofitting such systems is expensive and for existing vessel the business case is usually weak. Another option is reading and reporting consumption on each significant speed or weather change. This is not considered practical. In the following sections, we will discuss an approach to overcome the problem by exploiting sensors and systems already present on all vessels.

While recording high-frequency fuel flow data is expensive, other data is usually available in high frequency through the vessel's ECDIS at low cost. Here, position, speed through water and wind sensor are usually connected. Often also RPM is available through NMEA. Speed through water can be substituted by speed over ground (from GPS positions) and current hindcast data.

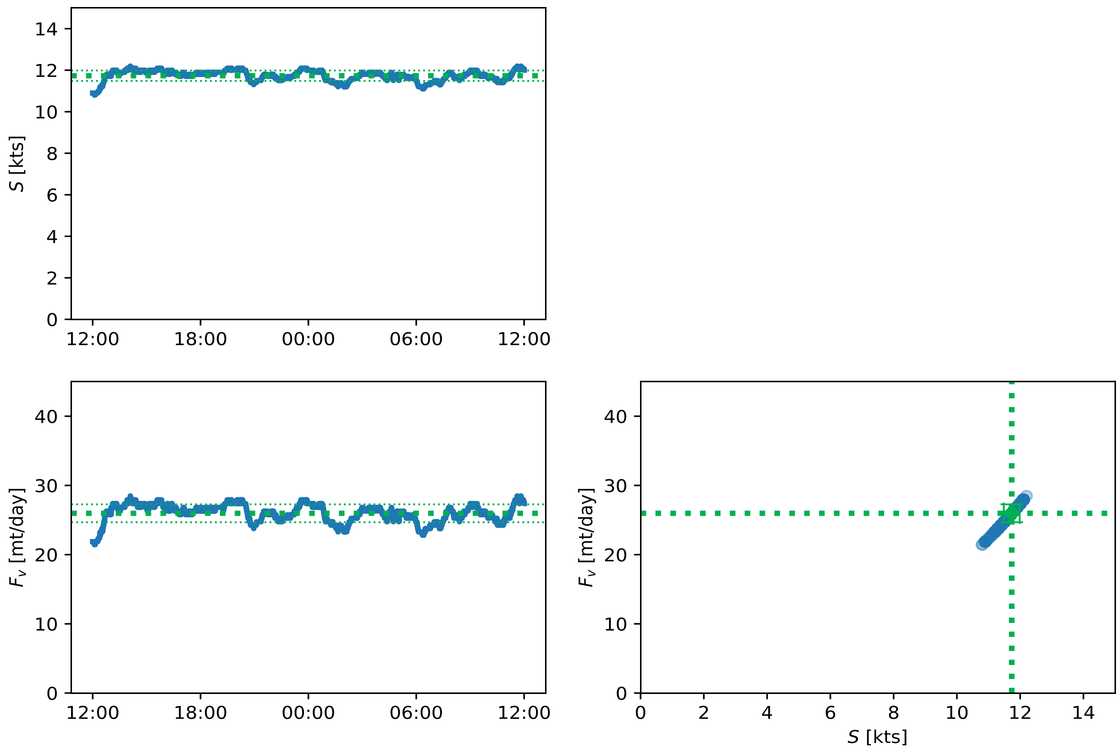


Fig.2: Timelines and speed consumption plot for one noon period with low variance. Aggregated values in green lying on the curve as expected.

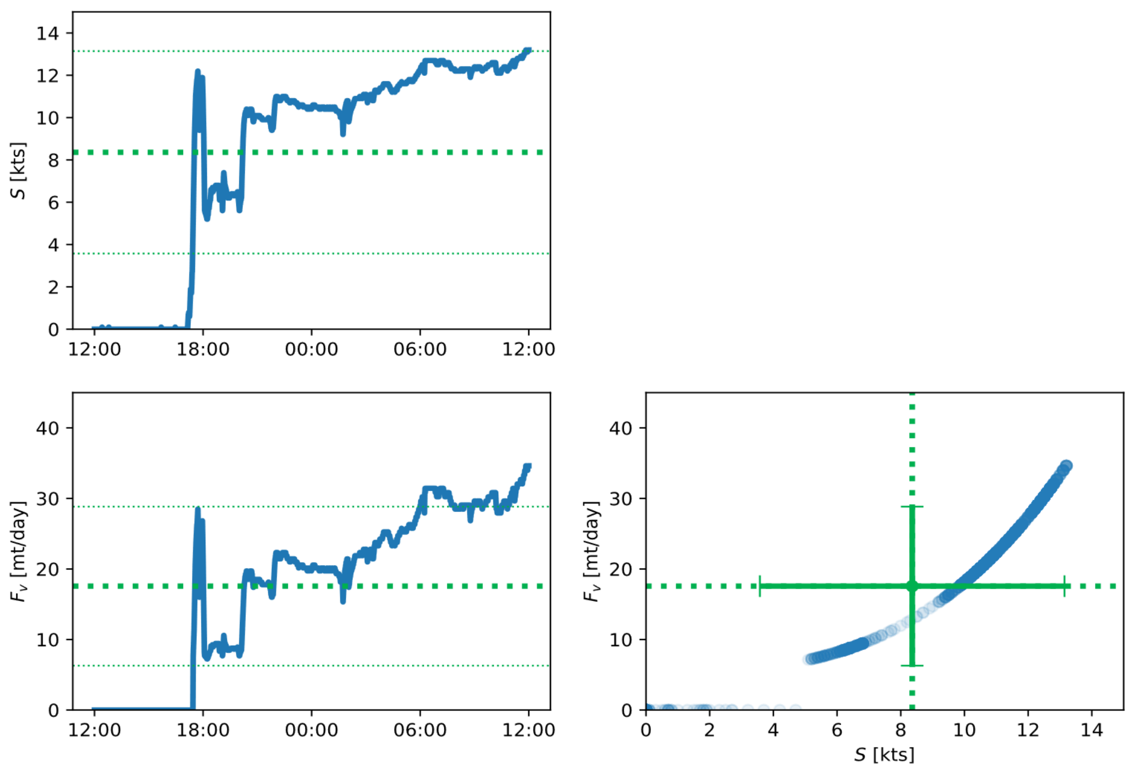


Fig.3: Timelines and speed consumption plot for a noon period with high speed variance. Aggregated values in green lying significantly above the curve. A large aggregation error is present.

Antola et al. (2017) presented a sensor fusion model that used speed over ground, forecast data, and average fuel flow from noon reporting. We will refer to this model as fuel flow model (FFM). In the following we will verify if the FFM is capable of removing the aggregation error from pure noon data.

3.1. Verifying the FFM

In this study, we apply an improved version of this model to synthetic data derived using our digital twin. We then compare the predicted performance with the known characteristics of our digital twin. Throughout this study we use speed through water. Knowing about the difficulties to measure, we will add a random error to the simulation later.

In the following we present and discuss result from this process:

1. define characteristics of digital twin (defining coefficients *a*,*b*,*c*)
2. generate realistic speed and draft (S_v,D_v) with desired statistical properties (high frequency)
3. compute high-frequency consumption F_v by applying 1 on 2
4. aggregate the F_v from 3 to noon periods which we denote $F_{v,N}$ (subscript N for noon)
5. apply FFM on $F_{v,N}$ from 4. and S_v, D_v from 2. To get prediction $\hat{F}$ (hat indicates prediction)
6. compare resulting high-frequency $\hat{F}$. from 5 with generic consumption F_v from 3

Remember FFM takes S_v,D_v (high frequency) and $F_{v,N}$ (noon) as input and delivers $\hat{F}$ (high frequency). We aggregate $\hat{F}$ to noon periods and call it $\hat{F}_N$, which we can compare against our input $F_{v,N}$.

Fig.4 plots the input data, Fig.5 the results of the simulation. The predicted values in blue do not match the synthetic input at the beginning. After about two week, the model has adapted and the results match the properties of the digital twin. Thus, we can conclude that the FFM works well after a short learning period.

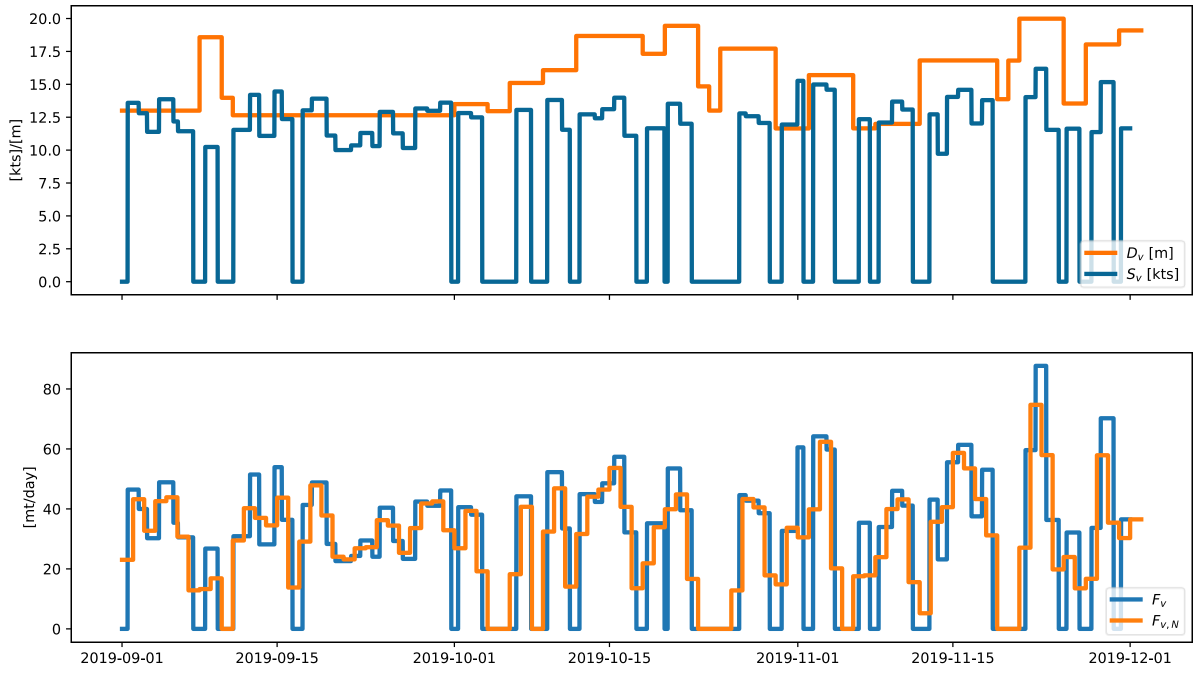


Fig.4: Synthetic input data used in this study: speed and draft (top), high-frequency fuel flow rate and noon aggregated (bottom).

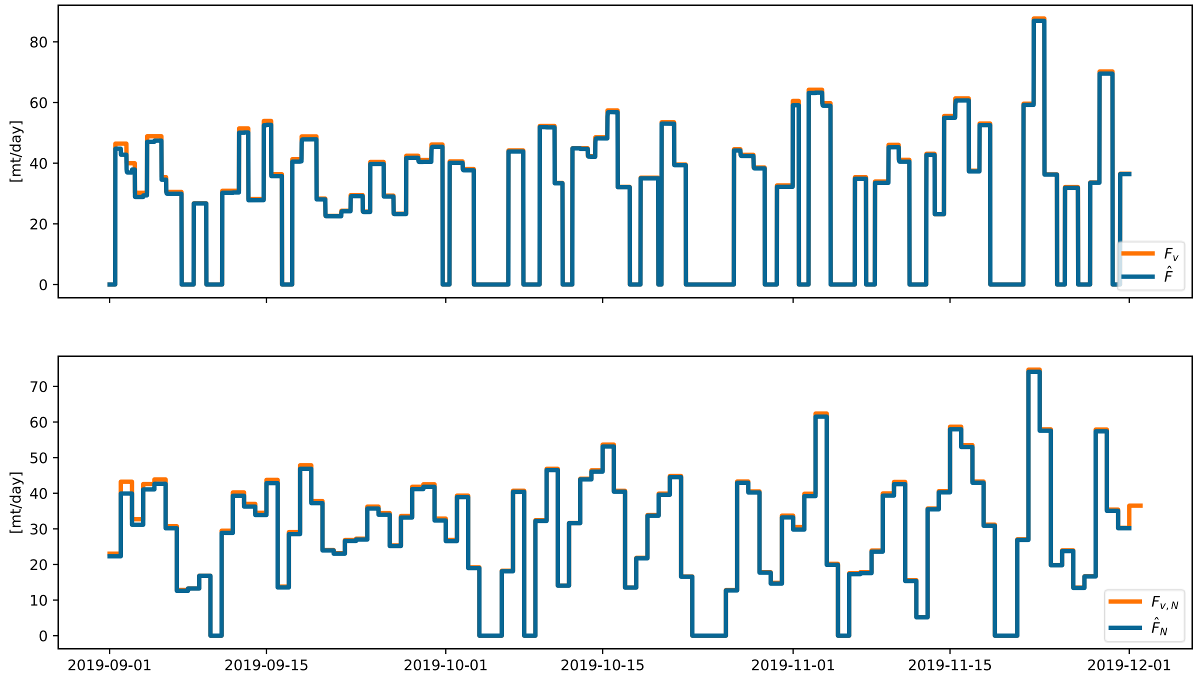


Fig.5: Comparison of digital-twin data (orange) and predicted data (blue) for high frequency (top) and noon aggregated data (bottom). FFM adapted to correct data after two weeks.

3.2. Effect of input errors on the FFM

In the last section we gave clean data without errors to the FFM. Real life data is typically affected by errors. In this section we add a Gaussian error with standard deviation of 3 mt/day to $F_{v,N}$ which becomes $F^*_{v,N}$ (start for error present) and a Gaussian error with standard deviation of 0.5 kn to S_v which becomes S^*_v. The manipulated input data is plotted in Fig.6.

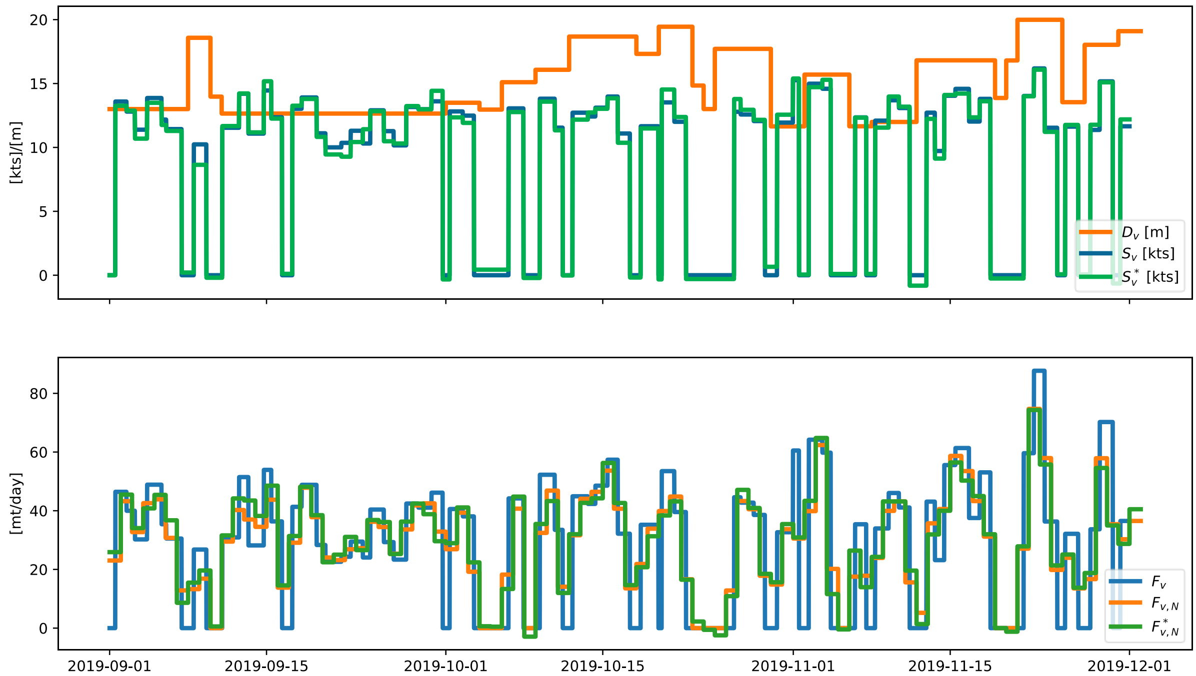


Fig.6: Input data with artificial errors added for speed (std=0.3 kn) and fuel flow (std=3mt/day) in green.

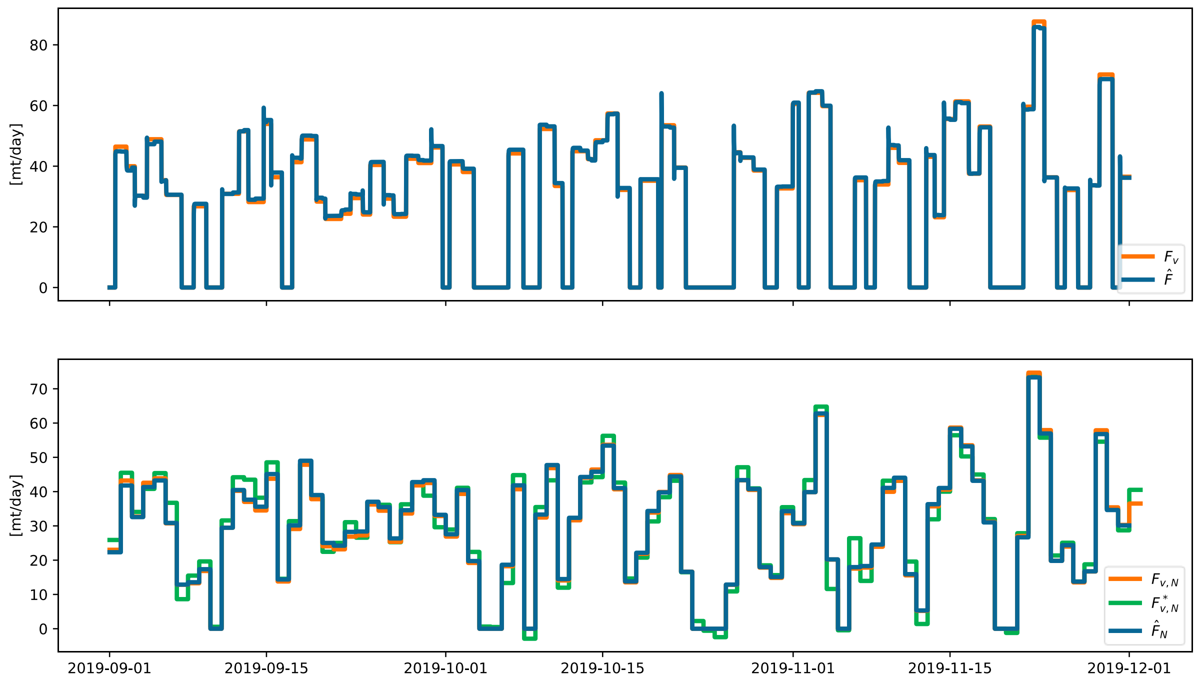


Fig.7: The predicted data (blue) is close to digital-twin data (orange) even though massive error was added to speed and consumption as indicated in green.

Appling FFP on S_v^*, D_v and $F_{v,N}^*$ results in predictions plotted in Fig.7. In the lower plot we added in green the manipulated input noon consumption $F_{v,N}^*$. Note the predicted values are close to "correct" data derived from the digital twin then to the input noon data. The model has eliminated large parts of the errors we added to the input data.

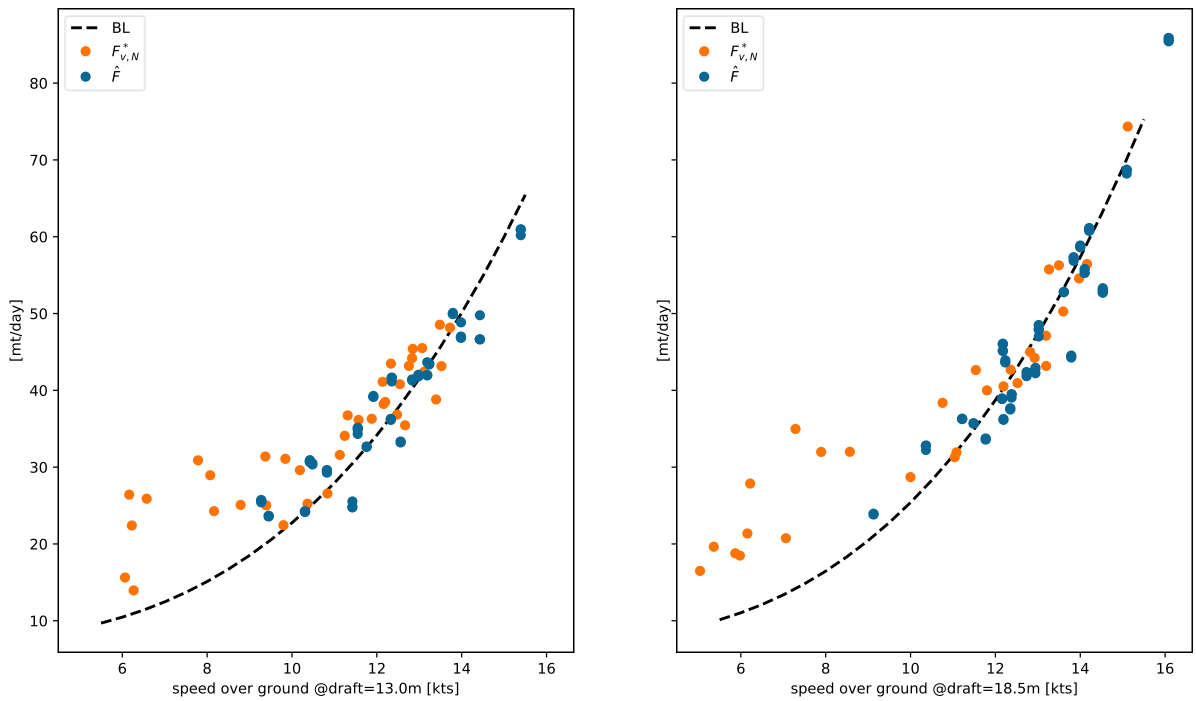


Fig.8: Noon aggregated data with errors (orange) and a sample of high-frequency modelled data (blue). Appling FFM has eliminated aggregation and reduced input errors. The dashed line is the true digital twin fuel curve.

The same result is plotted as speed-consumption relation in Fig.8. Data is filtered for two drafts. We plot noon data used as input S_v^* and $F_{v,N}^*$ together with a random subset (same size as noon data set) of the modelled high frequency data $\hat{F}$. The dashed line is the digital-twin true speed fuel curve. The orange dots indicate a systematic bias towards higher consumptions. The modelled values are all close to the expected digital-twin values plotted as dashed curve. The FFM has reduced the error of the input data without knowing the digital-twin properties. Since the FFM has learned the effect of the draft we can now normalize $\hat{F}$ to the respective draft as displayed in Fig.9.

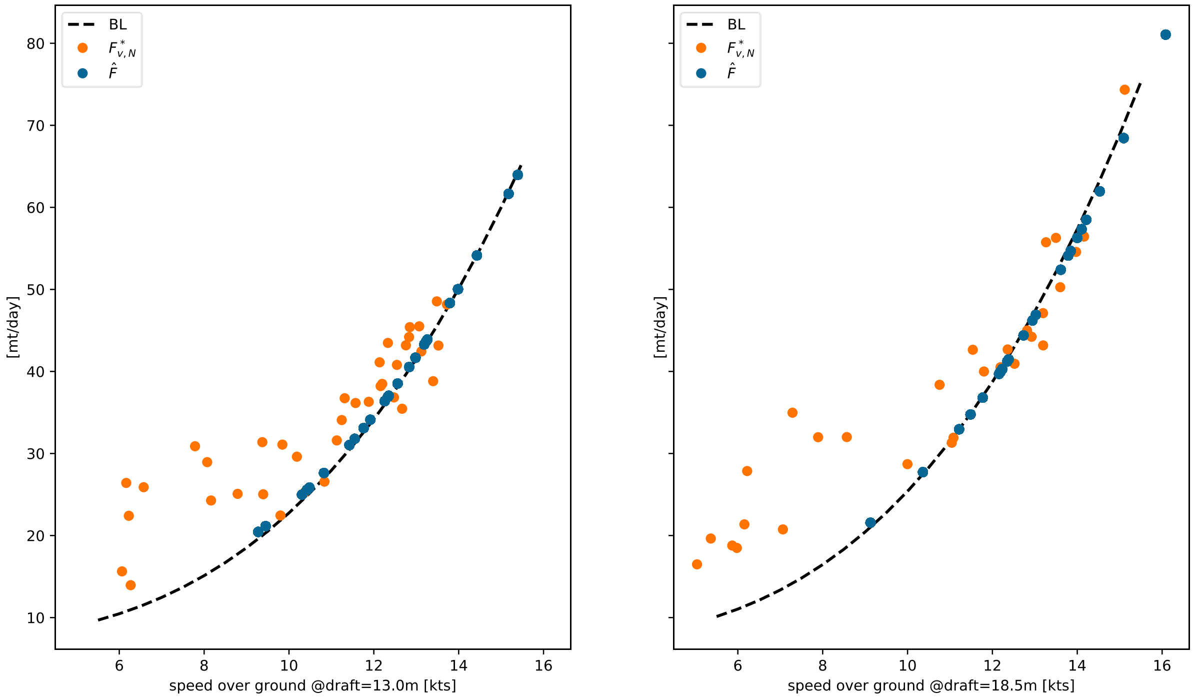


Fig.9: Noon aggregated data filtered for draft (orange) and high-frequency data normalized for draft based on FFM (blue). Here FFM has reduced and eliminated errors and the effect of varing draft.

3.3. Tracking hull fouling over time

Finally, we add a time-dependent term to our digital twin to simulate hull fouling.

$$F_v(S, D, t) = [a + (b + cD)\, S^3]\; e\left[\frac{t - t_{begin}}{t_{end} - t_{begin}}\right]^f$$

t is the time, and e and f are additional model coefficients.

We simulate three scenarios over one year:

a) constant hull performance
b) linear increase of consumption by 30% per year
c) and exponential increase of 30% within this period.

Fig.10 shows the simulated consumption at design draft and design speed over time. The predicted consumption follows the characteristic of the digital twin well. Comparing the clean input case with the one where we have added errors, we see the model adapts with some delay in the latter case. Considering the large errors, we added and the high fouling rate towards the end of c), the result is still very good.

4. Conclusions and outlook

Aggregation errors are always present when varying variables are aggregated over a noon-to-noon period. These errors are systematic bias which cannot be removed by simple averaging.

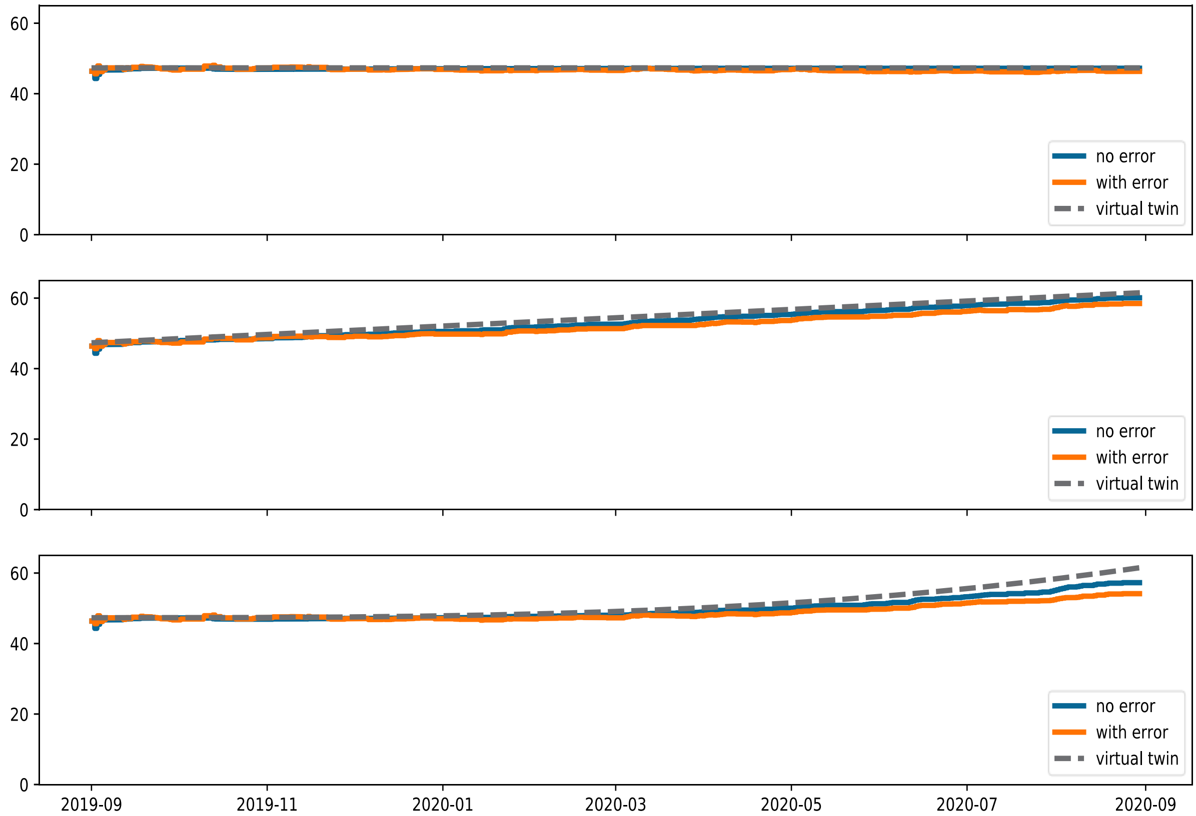


Fig.10: Fuel flow rate at design speed and draft over time. Three fouling histories plotted over time. Grey dashed it the characteristic of the virtual twin data feeded into the simulation. Blue the clean data, orange the on with random erros added. The FFM follows the development in time well. Presence of errors in the input retards the prediction slightly.

We successfully verified the FFM (fuel flow model) presented by *Antola et al. (2017)* and proved that the model can eliminate the aggregation error.

Under simplified conditions the model captured the vessel characteristics with regards to speed, draft and fuel consumption after a period of two weeks. We also investigated the robustness of the model by adding large errors on the input data (speed and fuel consumption). The result show that the model is able to eliminate these input errors successfully.

By adding a time-dependent factor to the input data, we also proved that the model can be used to track long-term trends such as hull fouling well.

The input data the model requires is available in sufficient quality on nearly all merchant vessels. Speed can be logged in high frequency by using existing navigational equipment. Weather can be obtained by hindcast. The fuel reading performed by the crew on noon-to-noon basis are typically imprecise. The discussed model proved to be robust against statistical errors.

The model presented here is a simplified version of the Wärtsilä Fleet Operations Solutions model. We have for example ignored the weather and other resistance terms. In a business setting this approach has proved to be robust and reliable, and we use it to predict hull fouling and check the quality of fuel consumption reporting e.g. for charter-party analysis.

References

ANTOLA, M.; SOLONEN, A.; STABOULIS, S. (2017), *The Art of Scarcity: Combining High-Frequency Data with Noon Reports in Ship Modelling*, HullPIC'17, Ulrichshusen, pp.118-123

SCHMODE, D., (2017), *Influence of Noise and Bias on the Uncertainty of Data-Based Hull Performance Prediction*, HullPIC'17, Ulrichshusen, pp.19-24

Index by Authors