TRIM AND BALLAST OPTIMISATION FOR A TANKER BASED ON MACHINE LEARNING

Big-data Analysis of Existing Data for Improved Environmental Performance and Ship Efficiency

21 DECEMBER 2020

RISE
Johannes Hüffmeier, Joakim Lundman, Fredrik von Elern

Project Information

Project title	Eco-efficiency to maritime industry processes in the Baltic Sea Region through digitalisation
Project Acronym	ECOPRODIGI
Authors	Johannes Hüffmeier, Joakim Lundman, Fredrik von Elern
Duration	39 months
Month 1	October 2017
Work package leader	Aalborg University, Chalmers University of Technology
Work package number/name	WP3: Solving eco-efficiency bottlenecks through digital solutions
Date of submission	21/12/2020

Revision

Revision no.	Revision Text	Initials	Date
V0.1	Draft Document, document structure	FvE, JH	25/11/2019
V0.2	Draft document, ML model and preliminary results	JH	25/06/2020
V0.3	Draft document, structure adjusted, results from presentations added, text on trim added, replaced journey with voyage, added finings, model descriptions and final results.	JL, JH	IN WORKS
V1.0	Report for review	JL. JH, FvE	30/11/2020
V 1.1	Layout, fonts. British language spellchecks. ARDEA photo replaced.	JL	21/12/2020

Executive Summary

Tank ships sail a large share of their time in ballast conditions, depending on their trading patterns up to half of the time at sea.

The aim of this project use case is to test the usage of machine learning and big data approaches based on existing historical ship operation data to improve energy efficiency on ballast trips. Founded on the analysis, guidelines on how to improve the energy efficiency of ships can be made by collecting real-time operational data.

The energy needed to propel a vessel is largely dependent on the total weight of it and of the speed it is operated at. Substantial savings in energy consumption and correspondingly to reduced fuel costs as well as to reduced emissions can be achieved by either lowering the speed or optimising the load taken onboard.

Ships are normally designed for optimal operation at one single or a few defined load conditions. By analysing off-design conditions (such as partial load, slower speed, and ballast conditions), significant improvements in efficiency can be obtained. Figures achieved by different means range typically from 10 to 40 percent by improving the crew's methods to load and operate the vessels, increasing resistance and delivered power [1]. Looking at operational regimes of tankers, the crews can only to a limited degree adjust the operational conditions for the loaded voyages when on hire, while when sailing off-hire or in ballast voyages allows for certain flexibility.

Building on a grey machine learning model with an underlying hydrodynamic model of the vessel, the data analysis provides a guidance to the mariners on summer ballast conditions that allow for fuel savings. The conditions derived by the model have been demonstrated by the shipping operator in full scale trials. Based on the analysis made, summer ballast conditions imply a reduction in fuel consumption in the range of 10-14% on the feasible trips.

Table 7 Savings in required power when sailing at 12 kts in different load and weather conditions.

VOY. NR.	38/20	45/20	39/20	44/20
TOTAL LOAD (APPROX.)	1500 ton	1670 ton	1870 ton	1920 ton
WIND CONDITION	Calm	Slight	Slight	Moderate
SAVINGS AT 12 KTS	14%	3,5–6%	7–9%	4–5%

The reduction in resistance and power needed to propel the vessel at 12 kts seems to be highest at light load conditions and in calm weather, which corresponds well with sound naval architectural theories.

Savings with reduced ballast do not only have an impact as savings when under way, but also lead to a reduced need for pumping of water into and out of the ballast tanks and for ballast water treatment plants both of which are energy consuming. Energy savings translate to positive reductions of both cost for fuel and in amount of emissions such as CO_2 and other GHG. Further strengthening the business case is the benefits of reduce load and run time on ballast water pumps and on the ballast water treatment system which reduces the costs for the upkeep of the vessel.

Besides the observations on the effect of ballast condition it was also noted that the effect of docking of the ship and cleaning of hull is clearly visible in data (>10% on power needed in the initial period afterwards). This can be used as an indicator for crew and management to plan hull cleaning.

Bitumen tankers such as ARDEA are designed to carry heated cargo and their tanks are heavily insulated, this gives them a lot of extra buoyancy compared to conventional tankers as they cannot have cold ballast water tanks adjacent to the heated cargo tanks. This implies even greater possibilities for ballast water optimisation on a larger conventional product or chemical tanker.

Based on the experience from building models and machine learning algorithms obtained in this study it is concluded that many times it is recommended to use simple and robust models such as decision tree random forest or variations of linear regressions. Grey box models are more complex to be implemented but might give faster results (shorter data collection period). A grey box model is not needed for all purposes. The accuracy is considered enough for most applications. The value of reliable, high resolution data and data processing is substantial. The methodology used in this study can be applied also in other settings and for other data processing. The benefit of collecting and processing operational and voyage data has large potential for quick pay-back on time and resources invested.

The study has been successful in bringing together the data from ship performance monitoring system, ship operations and naval architectural knowledge. It has set up models for canvasing the data and identifying low hanging fruit in energy efficiency that is of much value to the ship operator. By giving crew and manager the possibility to get real-time feedback on the effects of adjustments in ships operational conditions they can better optimise the energy consumed on board. The results and recommendations have been put together in guidelines for improved energy efficiency based on collected data relating to both improved decision support tools and for ship operational procedures.

ECOPRODIGI is an Interreg project increasing eco-efficiency in the Baltic Sea region maritime sector by creating and piloting digital solutions in close cooperation between industry end-users and research organisations. The aim of one of the project use cases is to test machine learning and big data approaches based on existing historical ship operation data to improve energy efficiency on ballast trips. Based on the analysis, guidelines for how to improve energy efficiency of ships can be made by collecting real-time operational data. The hypothesis was that a reduction in resistance leads to reduced power needed in light ballast conditions.

Contents

1. Introduction Big-data analysis of existing data for improved environmental performance and ship efficiency

Our approach is that there is more and more data collected on ships, but the added value and operational changes made possible by the data has been limited so far in shipping. Considering the data analysis as the crucial part allows for substantial savings. We limit ourselves at this stage to ballast voyages as these are not as contractually binding as loaded voyages when it comes to speed reduction, etc.

1.1 Background

All forms of transportation impact the environment in one way or the other. Regardless of how a shipowner decides to handle the environmental impact from his shipping activities the benefit of energy conservation should be seriously considered. Reducing the energy used corresponds directly to reduced cost savings as well as emissions. When adding abatement technologies or switching to alternative energy sources the cost of operations increases as the oil-based fuels are less costly.

Besides higher utilisation and filling grades, one of the ways to improve energy efficiency is to limit the amount of energy consumed per hour and goods transported. This study focuses on identifying and quantifying best practices in operations based on data logged onboard.

The energy needed to propel a vessel is largely dependent on the total weight of it and of the speed it is operated at. Substantial savings in energy consumption and correspondingly to reduced fuel costs as well as to reduced emissions can be achieved by either lowering the speed or optimising the load taken onboard when on ballast voyages. Besides the direct savings in energy needed for pumping and treating ballast water there are indirect savings of sailing in a lighter condition with less weight onboard as the submerged area or wet surface of the vessel is smaller at lower drafts.

Specifically, the energy usage related to ballast water operation is studied in more detail, as ballast neither contributes to the ship owners' profit nor adds any value to the transport system. The potential impact of ballast water handling is deemed as rather low in the shipping industry.

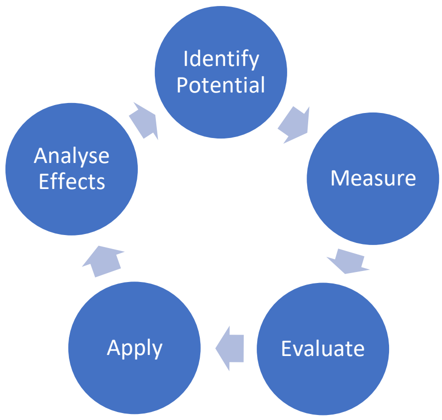
1.2 Aim and Scope

Purpose of the study is to demonstrate how value for business as well as for emission control can be created from auto-logging of high frequency operational data from ships.

The aim of the use case is to use machine learning and big data approaches based on existing historical ship operation data to improve energy efficiency on ballast trips and what else can be learned when adding additional data. Based on the analysis, guidelines for how to improve energy efficiency of ships can be made by data collected from real-time operational data.

1.3 Method

The study has followed a basic interactive method of identifying a potential for improvement, finding ways to measure the data, evaluate the data, apply improvements, and analyse the effects. The conclusions can then be the basis for further improvements.



The method consists of the following parts:

1) Data quality checks (anomaly detection, filtering)
2) Building a hydrodynamical model for machine learning
3) Machine learning of model derived above, regression analysis and optimisation based on ballast and trim
4) Analysis of results based on different optimisation approaches in order to achieve optimised ballast water intake and trim
5) Dedicated ballast conditions tested on ARDEA based on the model prepared by RISE/SMTF
6) Uncertainty analysis and recommendations for future development
7) Derive general guidelines based on the analysis performed and describe potential for energy savings

1.4 Delimitations

The analysis and guidelines are based on the data available from the studied ship. The data is collected by existing performance monitoring system and its selection and installation has not been a part of the study.

Missing data sources that have an influence on the required power and resistance such as currents, etc. are not included in the analysis. When impact is known and assumed to have a substantial effect (such as in situations when the vessel is travelling on rivers) such data has been excluded. The effect of fouling and marine growth has not been included in the analysis of ballast journeys.

Physical trials have been partly performed; continuous tests could not be performed due to manning situation onboard the vessel when crew changes are affected by COVID-19 restrictions.

The study focuses primarily on ballast voyages as these are not as contractually binding as loaded voyages and allow the Master larger discretion when it comes to speed reduction, etc.

2. Operational and Technical background

2.1 Ship Operation Optimisations Studied

Ballast Optimisation

A ship's purpose is the carriage of cargo from one port to another, not ballast. Ships are usually designed to carry the maximum amount of cargo within given constraints. As the flow of goods normally is unbalanced a ship will arrive with a full load of cargo, but seldomly leave as heavily loaded. In the case of tanker shipping and the carriage of wet bulk products a tanker will frequently leave the port of discharge without any cargo at all. As the ship will be lighter it will lay shallower in the water and have a smaller draft, this will affect the vessels hydrodynamic and seakeeping performance. However, to improve the vessels seakeeping the crew will take onboard seawater as ballast and this is thus referred to as a voyage in ballast condition. The amount of ballast water taken onboard is rarely standardised or dictated by written guidance or computer support. It will be more dependent on the individual crews experience from previous sailings and on the weather and sea conditions expected on the coming voyage. Or simply on the available volume of the ballast tanks. When adverse weather conditions and sea states are expected it is good seamanship to load the vessel as much as possible and increase the draft to improve the stability, pitching period, rolling period and vessels seakeeping. However, during calm weather and sea states it is possible to sail the vessel with a lesser amount of ballast onboard for as long as the manoeuvrability of the ship is maintained. Tankers are in loaded conditions typically course-stable and in ballast conditions course unstable.

By considering the off-design conditions (partial load, slower speed and ballast conditions), significant improvements in efficiency at these other design points may be realised with little or no impact on the design draft performance. For example, the Hamburg Ship Model Basin (HSVA) reports a 12 to 16 percent improvement in resistance and delivered power for a 70 percent design draft, 80 percent design speed condition. This was achieved by optimising just the bulb and extreme forebody, without any loss of performance at the design condition. This gives an indication on how large variations can be achieved by optimising the conditions. The speed differential between the full load condition and ballast condition for tankers built in the last ten years ranges from about 0.7 knots to 1.2 knots. [2]

Trim optimisation

A vessels trim is the difference in draught between the aft and the fore of a vessel. At even keel the vessel is uniformly submerged in water while a positive trim is when the vessel is lighter in the forward part and the vessel has a reclined posture in the water, while a negative trim is the opposite, the forepart is deeper in the water than the aft. Changing the trim of a vessel while keeping the same displacement is called trimming the vessel. Optimal trim is when the power needed at a certain displacement and speed is lowest compared to other trim angles. Optimising a vessels trim in the water has proven to have significant effects on the hydrodynamic flow along the hull and results in improved or degraded speed-power relations. It is not uncommon for energy saving of 10% or more between favourable and unfavourable trims [3] [4]. Trim optimisation is often performed based on model tests. Restrictions of optimum trim are given by the general arrangement of the vessel, where cargo, fuel, freshwater and ballast tanks' size, and positions only allow for certain trim angles.

Ballast water intake

The project team's experience is that the energy consumption impact off ballast water intake on board tanker vessels is not commonly considered by the vessels crew and master. The normal procedure is to fill the vessel's ballast tanks to 100%, with reference to weather and vessels manoeuvrability. However, shipowners confirm that fuel consumption will rise with more ballast onboard. This is due not only to increased energy need for propulsion due to increased weight and friction, but also on energy needed for ballast water treatment. The scope to use big data analysis for better energy efficiency is interesting for the shipowners. Short interviews with two technical managers for ship owners (Ektank AB and Furetank AB) confirms this view [5].

Operational energy conservation requirements

Regulatory measurements to monitor shipping's emission of greenhouse gases (GHG) have recently been introduced in parallel by both the IMO (International Maritime Organisation) and the European Union. The EU MRV-scheme (Monitoring, Reporting and Verification) focuses on CO_2-emissions while the IMO DCS (Data Collection System) gathers data on fuel consumption on a high level. Initially both schemes only stipulate monitoring and reporting, and no mechanism for curbing or penalising emissions and energy usage. CO_2 and other GHG emissions can be lowered either directly by lowering the energy consumption onboard (operational or technical), changing fuel type or indirectly by usage of various abatement technologies. Data collection systems as the one used in this project provided by Blueflow, cannot only be used for data collection, but even for reporting according to the rules and regulations above.

Energy conservation requirements for newbuilding

Since 2011 all newbuildings are essentially required to meet the Energy Efficiency Design Index (EEDI) for new ships, and the Ship Energy Efficiency Management Plan (SEEMP) as regulated in The "International Convention for the Prevention of Pollution from Ships (MARPOL 73/78). The index relates emissions of CO_2 to the preformed transport work and is calculated differently depending on ship and cargo type. The IMO legislation on the EEDI is currently moving into its 4th and last phase aiming to increase energy efficiency by up to 30% in 2025 on newbuildings compared to 2013 basis.

The latest official evaluations [6] show that most ship types, despite large container vessels, have just improved efficiency by only up to 3%. The drivers towards reduced emissions are therefore probably found in operational measures including ship speed.

2.2 ARDEA – Vessel details

Figure 1: ARDEA Bitumen tanker alongside in 2012. Credits: Crew Chart Ship management AB.

The following details are fetched from the Clarkson intelligence system, unless stated otherwise. ARDEA is an asphalt/ bitumen tanker with the following dimensions:

Main particulars

Length over all	(m)	99.9
Length, pp	(m)	95
Beam	(m)	16
Breadth mld.	(m)	15.86
Length over all	(m)	99
Design draught	(m)	5.7
Gross Tonnage:	(m)	4621
Deadweight	(t)	4972
Year of build		2012
Depth mld.	(m)	9.0
Draught design	(m)	6.1
Draught scantling	(m)	6.5
Cargo capacity	(m^3)	4 300
HFO tanks	(m^3)	350
DO tanks	(m^3)	75
FW tanks	(m^3)	60
Water ballast	(m^3)	2 000
Main engine	(kW)	4 000
Aux engines	(kW)	3 x 590
Shaft generator	(ekW)	760
Bow thruster	(kW)	700
Cargo pumps	(m^3/h)	4 x 350
Ballast pumps	(m^3/h)	2 x 400
Accommodation	(pers)	16 pers
Service speed (7.8m) 85% MCR	(knots)	14.0

Standard Details

IMO Number 9503902, Built at Wuhan Nanhua HJ delivered in Apr 2012, BV Classed, Ice Strengthened IA Class, Design FKAB I12 by FKAB.

Specialist Details

Cargo Capacities of 4,300 m3. and 27,046 Barrels.

Equipment Details

MAIN ENGINE 1 x Diesel - Ningbo C.S.I. Power G6300ZC16B - 4-stroke 6-cyl. 300mm x380mm bore/stroke 4,000mkW total at 600rpm.

AUXILIARY 3 x Aux. Diesel Gen. - Caterpillar 3412C - 4-stroke 12-cyl. 137mm x 152mm bore/stroke 1,770mkW total at 1,800rpm driving 3 x ac generator(s) at 1,770ekW total, (2,212.50kVA total) 440V at 60Hz.

OTHER POWER EQUIPMENT 1 x Shaft Generator (PTO) at 760ekW total, ac, 440V at 60Hz.

PROPULSOR 1 x CP Propeller (Aft Centre) (mechanical) (Bronze), 153rpm. Diameter: 3700 mm [*Ref: Ship management*]. POS, PROPULSOR 1 x Pos, Tunnel Thruster (Fwd.) (electric) at 700ekW total AC.

Eco Details

ENVIRONMENTAL EQUIPMENT 1 x BWTS - Ballast Water Treatment System - Alfa Laval PureBallast 2.0 Ex 500. 100 – 500 m3/hr @ 132kWh.

The total power consumption for Ballast Water Treatment System and 1 Ballast Pump is 187 KW. Ballasting and De-Ballasting operation make almost the same power consumption as both operations utilise both AOT unit. ARDEA Ballast pump capacity for 1 pump is 400 m3/hr at 3.5bar [7].

Specific Fuel Oil Consumption:

Main Engine: SFOC 203 g/kWh [8].

Gensets: SFOC 200 g/kWh [7]

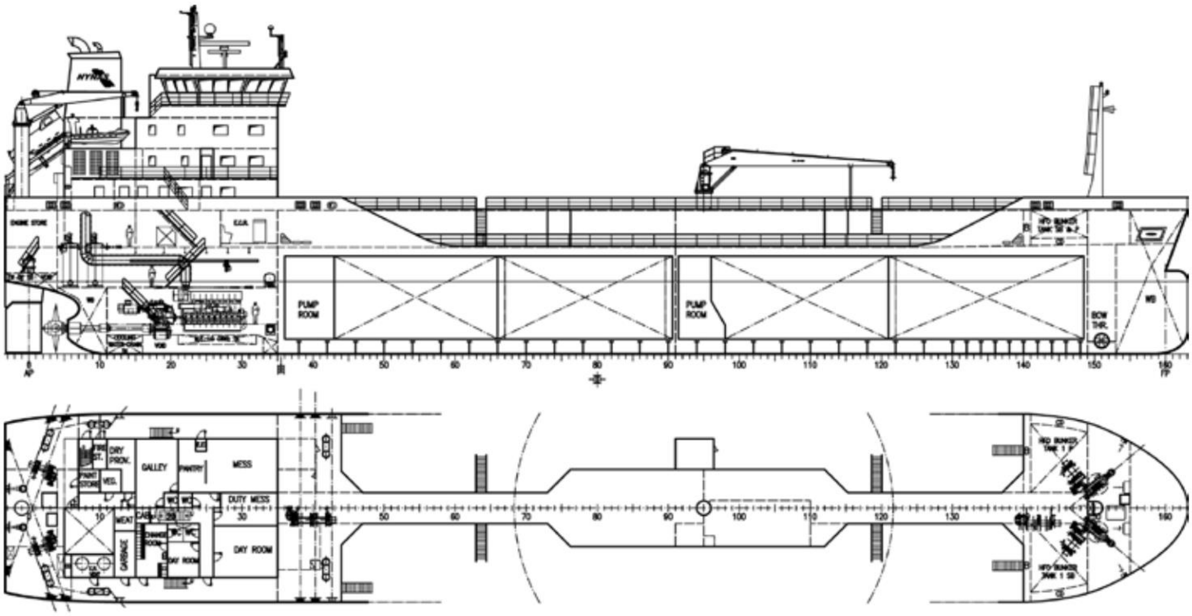


Figure 2: General arrangement based on FKAB basic design, Source: Product sheet by FKAB [9]

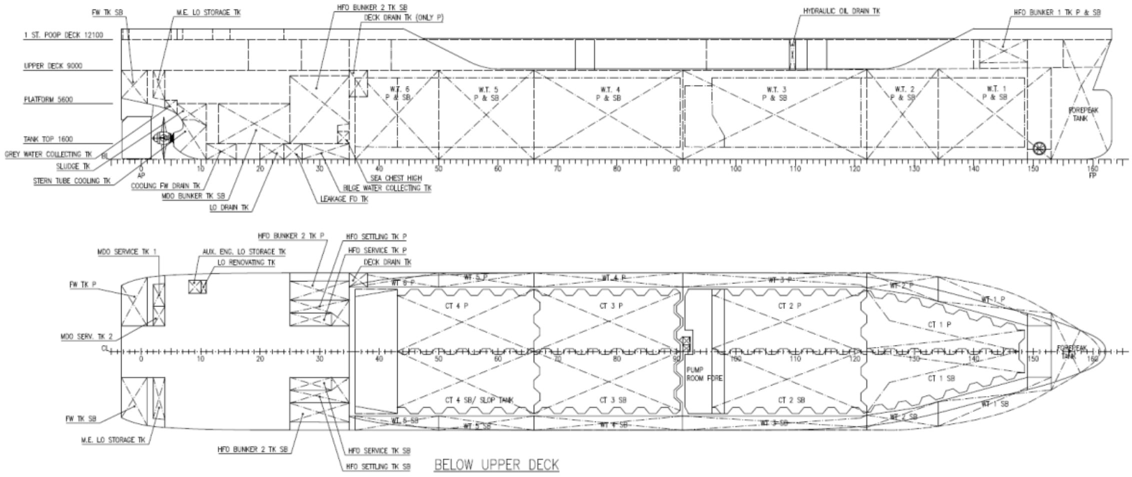


Figure 3: Tank plan of ARDEA showing locations of ballast tanks

Characteristics of bitumen tankers

Bitumen tankers such as ARDEA are designed to carry heated cargo and their tanks are heavily insulated, this gives them a lot of extra buoyancy compared to conventional tankers as they cannot have cold ballast water tanks adjacent to the heated cargo tanks. To compensate they need additional ballast water capacity which results in a ballast-to-cargo relationship for ARDEA 2000 ton / 4972 dwt or 40%. For a typical product/chemical tanker the relationship is approximately 45% of the deadweight as less potential cargo space is lost in insulation. This implies even greater possibilities for ballast water optimisation on a larger conventional product or chemical tanker.

The vessel as such is small and has a limited possibility to vary trim angles in ballast conditions due to the tank arrangement that is used for ballasting, as shown in the figures above (general arrangement and tank plan). If certain tanks are used for ballasting, the propeller is no more completely submerged which results in poor propulsion efficiency.

Trading routes

M/T ARDEA is trading in Northern Europe. Ports of call are predominately in the North Sea and the Baltic Sea, some voyages in the studied period were towards destinations somewhat further away such as to Iceland.

Figure 4 Area of operation - typical voyages of M/T ARDEA. Data from BlueFlow system.

2.3 Data collection, parameters, and data quality

Data logger used

The project has made use of an existing data collection platform linked to the vessel. The platform is provided by Blueflow Energy Management.

The energy management system helps to manage the vessels energy sources. It presents consumption and energy efficiency data on graphical user interfaces onboard the vessel. It collects and sends data to a cloud platform for secure storage and data analysis. The system consists essentially of two parts, Blueflow Online and Blueflow Onboard.

The Onboard module integrates with various other onboard systems and flowmeters to monitor fuel and energy consumption and other parameters in real-time. Parameter data are sent to an online service for reporting, analysis and verification. These findings can be used to reduce energy consumption, make diagnostics, take comprehensive reports and increased knowledge of a vessel's performance.

In this project, only the Blueflow online data have been used. [http://www.blueflow.se/]

Input data

Data has been provided by the ship owner operating bitumen tankers with 1 second resolution covering various energy consumers, load cases and environmental parameters under 69 months. Existing data has been extracted to compare fuel consumption in relation to ballast and trim.

Parameters used are:

- Time
- SOG - Speed over ground
- UKC - Under Keel Clearance
- Trim and list [deg]
- Heading [deg]
- Location (Latitude and Longitude) [deg]
- Ballast weight (ton) – total value, no distributed information (tank locations)
- Fresh water (ton) – total value, no distributed information (tank locations)
- Fuel onboard (ton) – total value, no distributed information (tank locations)
- Total load [ton] – total value, no distributed information (tank locations)
- Power output Main Engine, [kW]
- Power output Shaft generator, [kW]

- Power output Auxiliary Engines [kW]
- Power output boilers [kW]
- COG, Course over Ground (course/heading)

Fuel oil consumption Main Engine (kg/h) Data quality

The data gathered by the energy performance monitoring system is extensive and detailed. It is deemed to generally be of good quality when checked. Some anomalies have been detected and those data points have been omitted from the study.

Unfortunately, there is no good measurements or data available for the currents on most commercial vessels. This was even true for ARDEA, which gives some uncertainties to the analysis and thus the effect of it on speed through the water and the energy consumption.

2.4 Calculation and Assessing the EEDI Index Ship Energy Efficiency for ARDEA

The reference EEDI is calculated by:

$$\text{Reference EEDI} = a*b^{-c}$$

For tankers, the following values are valid [10]:

a = 1218.80
b = DWT = 4972 t
c = 0.488

This results in a **reference EEDI value for ARDEA of 19.14367 gCO_2/ton.mile**

ARDEA's trading area is primarily within the SECA (Sulphur Emission Control Area) and she runs mainly on marine diesel oil. Emissions based on the consumption from the vessel per nautical mile are therefore calculated based on the following values given in the 2018 EEDI guidelines [11]:

Table 1 Carbon content and specific energy for different marine fuels according to 2018 EEDI Guidelines.

Fuel type	Carbon Content	*EFf* (g CO_2/g fuel)
HFO	0,8493	3,114
MDO	0,8744	3,206
LNG	0,7500	2,750
Methanol	0,3750	1,375
LSHFO 1.0%	0,8493	3,114

Due to the specific requirements for vessels to be classed and suitable for trading in ice-infested waters the EEDI requirements include specific adjustments related to vessels that are ice classed according to the Swedish-Finnish Ice Class, see Table 2. ARDEA fulfils the requirements for Ice Class IA.

Table 2 EEDI coefficients for Ice Classed vessels.

Ship type	f_{i0}	$f_{i,max}$ depending on the ice class			
		IA Super	IA	IB	IC
Tanker	$\frac{0.00138 \cdot L_{PP}^{3.331}}{capacity}$	$2.10 L_{PP}^{-0.11}$	$1.71 L_{PP}^{-0.08}$	$1.47 L_{PP}^{-0.06}$	$1.27 L_{PP}^{-0.04}$
Bulk carrier	$\frac{0.00403 \cdot L_{PP}^{3.123}}{capacity}$	$2.10 L_{PP}^{-0.11}$	$1.80 L_{PP}^{-0.09}$	$1.54 L_{PP}^{-0.07}$	$1.31 L_{PP}^{-0.05}$
General cargo ship	$\frac{0.0377 \cdot L_{PP}^{2.625}}{capacity}$	$2.18 L_{PP}^{-0.11}$	$1.77 L_{PP}^{-0.08}$	$1.51 L_{PP}^{-0.06}$	$1.28 L_{PP}^{-0.04}$
Containership	$\frac{0.1033 \cdot L_{PP}^{2.329}}{capacity}$	$2.10 L_{PP}^{-0.11}$	$1.71 L_{PP}^{-0.08}$	$1.47 L_{PP}^{-0.06}$	$1.27 L_{PP}^{-0.04}$
Gas carrier	$\frac{0.0474 \cdot L_{PP}^{2.590}}{capacity}$	1.25	$2.10 L_{PP}^{-0.12}$	$1.60 L_{PP}^{-0.08}$	$1.25 L_{PP}^{-0.04}$

As ARDEA was built 2012, before the requirements came into effect 1st January 2013, she is not subject to them. However for comparison the **EEDI for ARDEA is calculated to 21,23** using Danish Shipping's EEDI Calculation tool [12] and verified by authors own EEDI calculations according to IMO MARPOL ANNEX VI regulations. Thus, ARDEA would not fulfil the stipulated EEDI-value had she been built after they came into effect.

EEOI Guidelines Circ 684

The Guidelines present the concept of an indicator for the energy efficiency of a ship and can be used to establish a consistent approach for voluntary use of an EEOI. It is supposed to assist ship-owners/ operators in the evaluation of the performance of their fleet with regard to CO_2 emissions. The Guidelines are only adversarial and present a possible use of an operational indicator.

Ship-owners are invited to implement either these Guidelines or an equivalent method in their environmental management systems.

$$\mathrm{EEOI} = \frac{\sum_j FC_j \times C_{Fj}}{m_{cargo} \times D}$$

- ***j*** is the fuel type
- ***i*** is the voyage number
- FC_j is the mass of consumed fuel *j* at voyage *I*
- C_{Fj} is the fuel mass to CO_2 mass conversion factor for fuel *j*
- m_{cargo} is cargo mass (tonnes) or work done (number of TEU, passengers, etc.) depending on ship type.
- ***D*** is the distance in nautical miles corresponding to the cargo carried or work done

EEOI is normally calculated for one voyage but an average EEOI for a number of voyages can be carried out as well.

The EEOI for ARDEA for the whole dataset is 0.4 kg CO_2/(tons x nautical miles), for the loaded voyages only 0.06 and for the ballast voyages 106.

2.5 Vessel Energy Consumption

Tankers and Bulkers in general operate at modest speeds between 10-15 knots and spend more time at layby or at anchorage waiting for charters compared to linear shipping services such as container and RoRo-ships. Bitumen tankers such as ARDEA are subject to the seasonal variations as the demand for asphalt is lower in the colder period of the year. This allows for more time on an annual basis for service and more frequent dockings of the vessel. This opportunity is used for hull cleaning and for de-coking (removal of built up solid residues of petroleum coke in the cargo tanks) which otherwise hampers the load intake.

Based on the voyage data collected the vessel spends around 44% in port/ at yard/ at anchorage, 30% on loaded voyages and 26% in ballast conditions. The share of time that the wind and wave conditions (wind < 6m/s) could allow for summer ballast voyages is 42% of the ballasted voyages or 11% of the total time.

In ballast conditions, the energy is consumed mainly for propulsion purposes (78%), for boilers (5.5%), for the auxiliary engines (10%) and for the shaft generator (5.9%).

In loaded conditions, the energy is consumed mainly for propulsion purposes (75.2%), for boilers (10%), for the auxiliary engines (14.5%) and for the shaft generator (0.3%).

There is a high variation of usage of auxiliary power. While the average in ballast conditions is about 16%, it can raise to up to 60% as maximum. These values are 19% and 64% in loaded conditions.

3. Machine Learning algorithms

The machine learning used in the project are consisting of an underlaying "physical" hydrodynamic model that is trained to the data. The hydrodynamic model and the machine learning algorithms used are described in the chapters below.

3.1 Model description

Various approaches have been used to model the vessel based on the data. The main steps that have been used are the data selection, pre-processing, transformation and interpretation/ evaluation, these are shown in Figure 5.

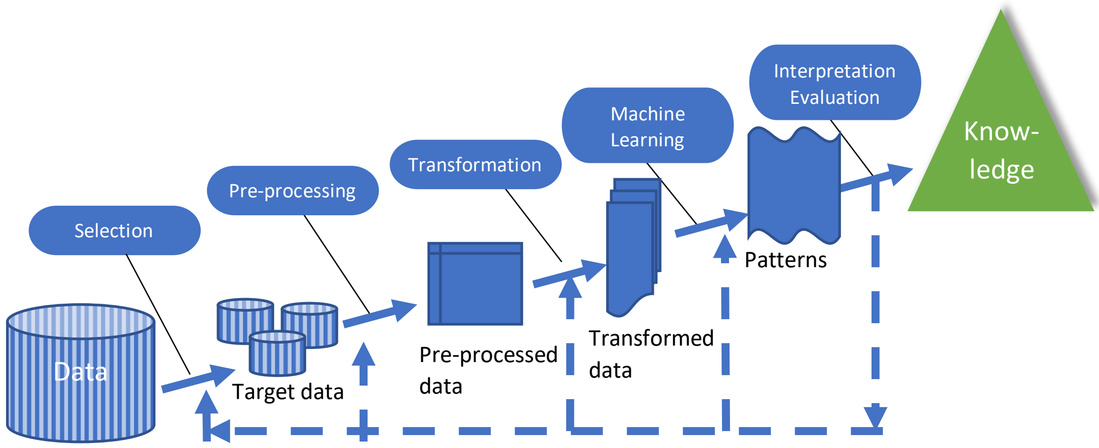


Figure 5: An Overview of the Steps That Compose the Machine Learning Process, adopted from [13]

Selection

The data selection was given by the main research question, i.e. optimised ballast conditions for reduced engine load and fuel consumption. Nevertheless, some of the tests in the project have also involved including the fully loaded vessel, to build a representative model of the vessel considering the ship properties for a model covering several load cases. The label to be predicted is the engine main delivered power of the vessel [kW] minus the load that is taking off by the shaft generator [kW]. Based on the data and correlations, there is a strong relation between fuel consumption, engine load and delivered power. Therefore, this has not been modelled separately.

Pre-Processing

The data from ARDEA have been averaged over 10 minutes, which is typically a statistical measure for a.o. environmental data and is deemed representative for a time span. It allows to remove outliers and short-term variations in data. It also gives an indication on the variability of the data, as the standard deviation for the 10 minutes interval where included as features. The data has then been filtered and "known" faulty measurements have been excluded (e.g. values above engine maximum load). The ship standing still has been removed from the data as well. The idling of the main engine has been removed from the engine loads, in order to only describe the engine load due to sailing of the vessel. A total 350 635 data points existed in the raw data, 164 194 entries remained for all loading conditions and 74 182 for the ballast conditions.

Transformation

The transformation of the data into a feature and label set of data was performed in this stage. In order to optimise the model accuracy, variations with the feature selection have been performed to describe the physics as much as possible in the regression models, while in the decision tree all "known" features have been included. In the following description, the following letters are used to describe feature and label:

X - Feature or predictors

Y – Label or response variable

3.2 Hydrodynamic model

Water resistance

The hydrodynamic model, being the base of the machine learning algorithm is based on a model for still water resistance in different draft conditions.

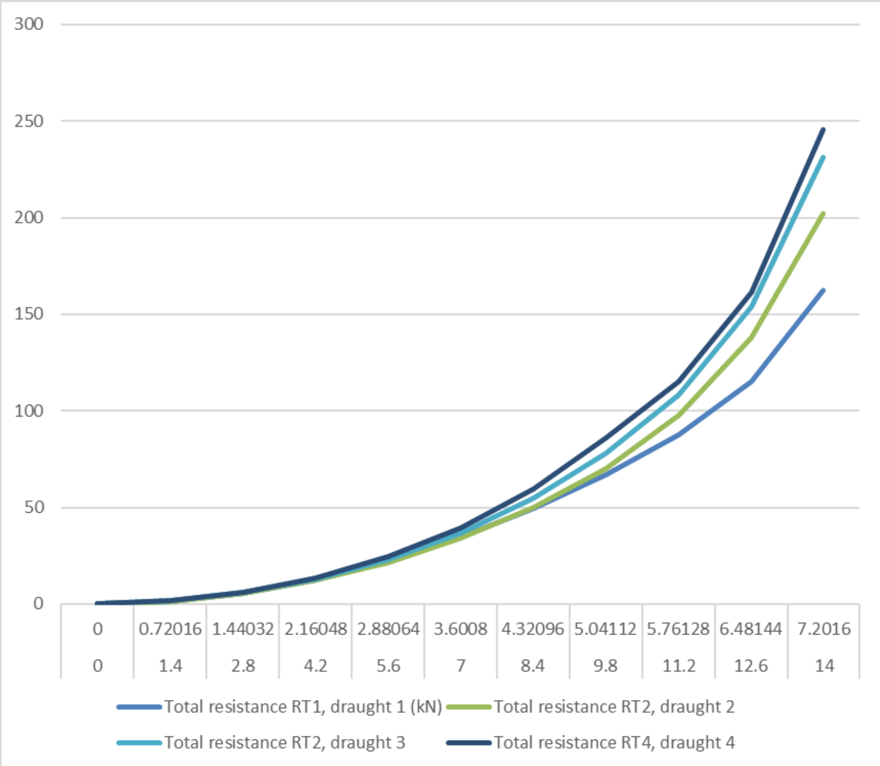


Figure 6: Ship resistance at deep water for different ballast conditions

The deep water resistance, R_{Tdeep}, is obtained by interpolating the curves in Figure 6, in which the deep water resistance for draughts of 0.6, 0.8 1 and 1.1 times the design draught have been à priori estimated, based on regression methods of publicly available ship resistance data. The draught of the vessel is calculated by assuming that the design draught corresponds to a total load of 4000 metric tons.

The water resistance in shallower water, R_T, is given by

$$R_T=(1+0.46 \text{ zet } F_{nh})\ R_{Tdeep}$$

where the shallow water coefficient, zet, is given by

$$\text{zet}=\frac{\text{draught}}{\text{h-draught}}$$

in which h is the water depth. The Froude number, F_{nh}, is defined as

$$F_{nh} = \frac{V}{\sqrt{gh}}$$

Added resistance in waves has been modelled based on the 10 minutes standard deviation of the trim change by the following function:

$$R_{AddWave} = (C_{AddWave} + C_{Trim}\ Trim_{std})\ \mathit{Displacement}$$

The total hydrodynamic or water resistance is then given by

$$R_{Total} = (R_{AddWave} + R_T)$$

Wind force

The water resistance term in the previous section is assumed to account also for the air resistance at still conditions. The additional force from wind is calculated through

$$F_{wind} = 0.5\ \rho\ V_{relative\ wind}{}^2\ A_{wind} C_X - 0.5\ \rho\ V_{vessel}{}^2\ A_{wind} C_X$$

Here $V_{relative\ wind}$ is the wind speed as measured on the moving vessel. The transversal cross section A_{wind} is set to 500 m^2 and the coefficient C_X is shown in red in Figure 7.

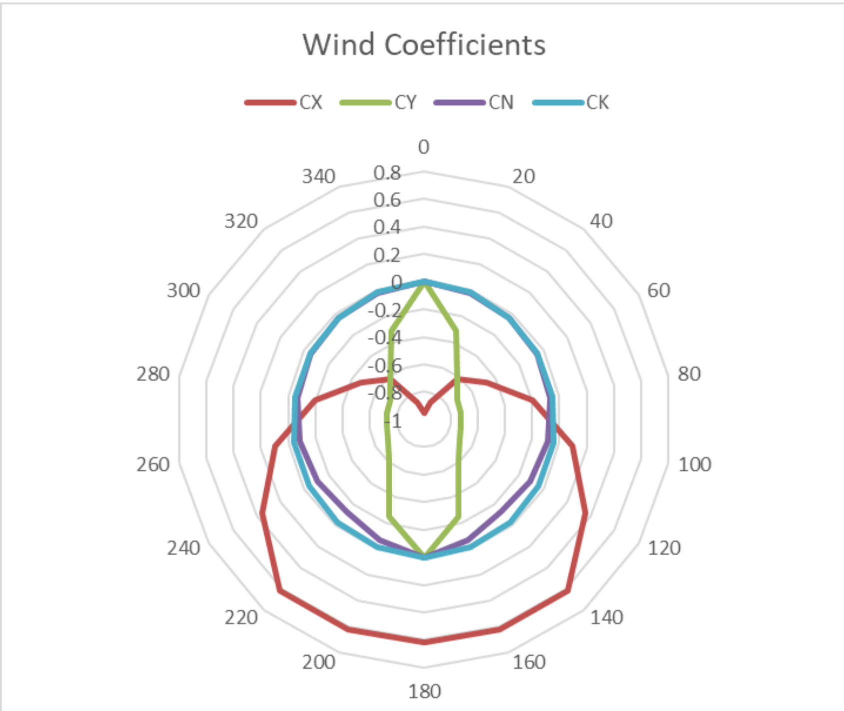


Figure 7: Wind coefficients used in the model.

Modelling the propeller

The variable pitch propeller is modelled through a somewhat simplistic relationship

$$C_T = C_{pitch} \frac{P_{0.7R}}{D} + C_\beta \beta$$

where C_T is the thrust coefficient defined by

$$T = C_T \, \rho \, 0.5 \left[V_A{}^2 + \left(0.7\pi \frac{RPM}{60} D^2 \right) \right] 0.25\pi D^2 \, ,$$

$P_{0.7R}$ is the propeller pitch and β is the advance angle given by

$$\beta = arctan2\left(0.7\,\pi \frac{RPM}{60} D, V_A \right).$$

Here the advance speed, V_A, of the propeller is set to

$$V_A = (1 - w)\, V_{vessel}$$

with w is set to 0.27 based on literature.

The afore-mentioned coefficients C_{pitch} and C_β are empirical to the model, and it is believed that these parameters compensate somewhat for errors in the estimates of some of other parameters (such as in the estimate of w above for example). In order to determine C_{pitch} and C_β it is assumed that no acceleration are present (as well as only very limited number force-contributions, most notably disregarding the impact of the sea state) such that

$$F_{thrust} = F_{resistance} - F_{wind}$$

where the thrust force, F_{thrust}, relates to the thrust, T by

$$F_{thrust} = (1 - t)\, T$$

where t has been set to 0.17.

We find that setting $C_{pitch} = 0.3$ and $C_\beta = -0.012$ gives reasonable agreement with the data.

Predicting fuel consumption

A typical use case for the model is to predict the fuel consumption of the vessel given the speed of the vessel as well as inputs such as the wind. In order to accomplish this, we need a way to translate between the pitch ratio $\frac{P_{0.7R}}{D}$ and the fuel consumption. Figure 8 illustrates that main engine power depends on a combination of propeller pitch and vessel speed. The actual model formulation is slightly convoluted since it instead uses a combination of $\frac{P_{0.7R}}{D}$ and β in order to predict an effective torque coefficient, C_Q, from which the engine power is calculated. The underlying principle is however very much the same as just fitting a 2-dimensional curve to the data in Figure 8. Figure 9 shows how a relation between fuel consumption and engine power can be derived directly from the data and this concludes the current model formulation.

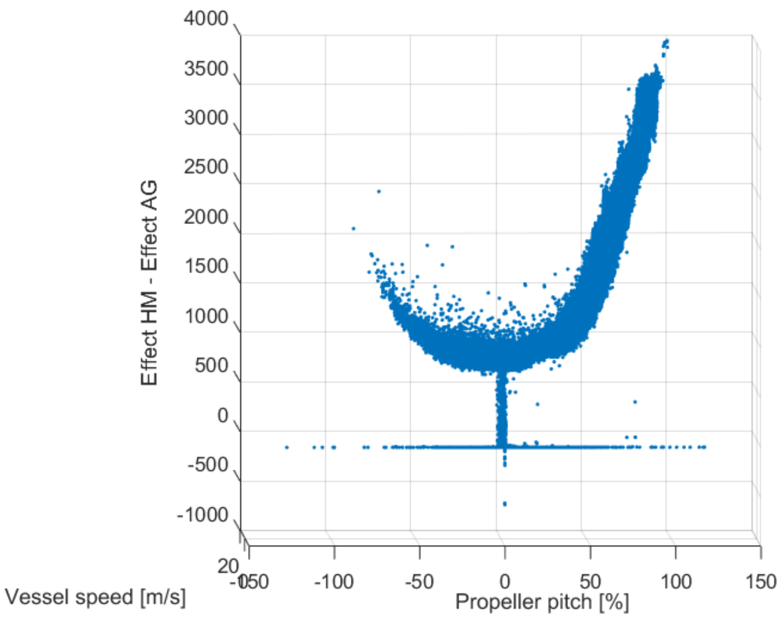


Figure 8: Predicting engine power from a combination of propeller pitch and vessel speed

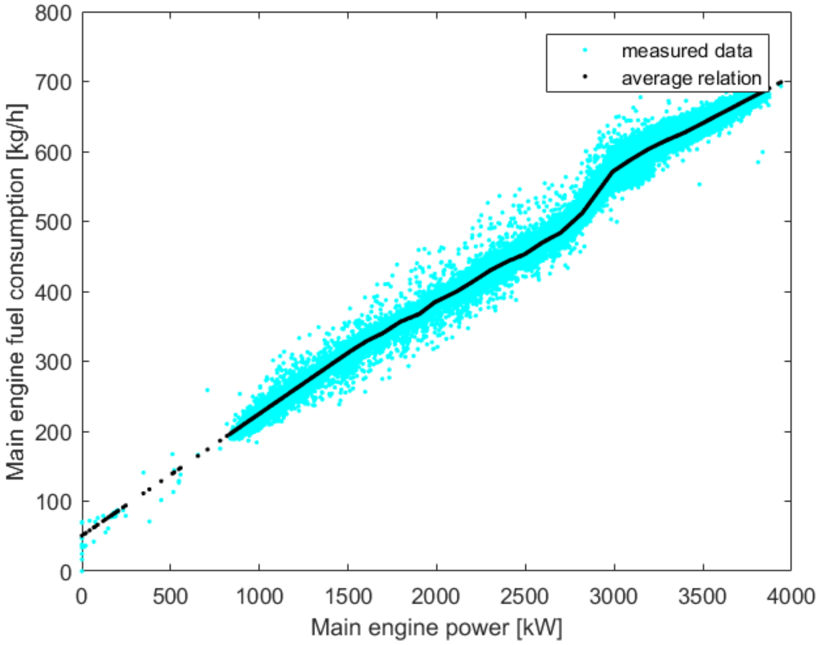


Figure 9: Predicting fuel consumption from engine power

3.3 Machine learning models

Based on the data various machine learning algorithms have been used. Different methods have been used to get a broad understanding, all from grey box models with an underlying hydrodynamic resistance model to traditional regression and black box models. These are described in short below. All use an approach as shown in the figure below:

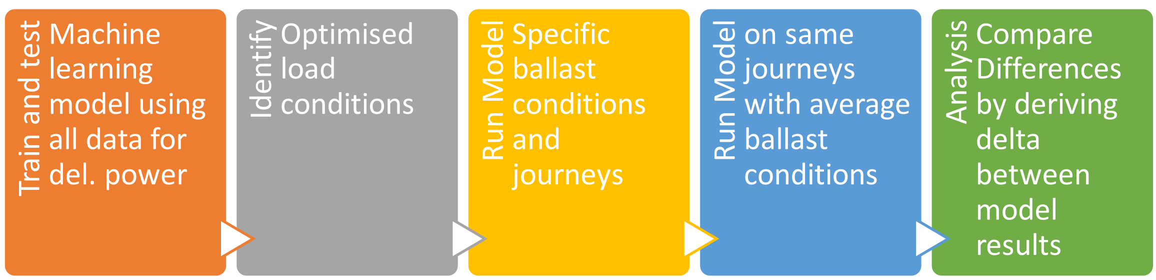


Figure 10: Approach for optimised ballast conditions analysis and savings

Grey Box Model

In mathematics, statistics, and computational modelling, a grey box model combines a partial theoretical structure with data to complete a more sophistical model. The grey box model consists of the hydrodynamic model described above as well as a regression model of the parameters used for the variables not used in the hydrodynamic model such as trim, detailed loading data, etc. This implies that the machine learning as such does not only use the data from the measurements, but also from the hydrodynamic model.

Linear Regression Models

Various analyses have been performed to derive best possible results. The features of the model have been varied as well as the algorithms for the linear regressions. Common for the linear regression models are that the Ordinary Least Squares procedure seeks to minimise the sum of the squared residuals. This means that given a regression line through the data, one calculates the distance from each data point to the regression line, square it, and sum all the squared errors together. This is the quantity that ordinary least squares seek to minimise.

The following different models have been explored:

1) **Linear Regression**
   Linear regression is a linear model, e.g. a model that assumes a linear relationship between the input variables (x) and the single output variable (y). More specifically, that y can be calculated from a linear combination of the input variables (x) and a possible constant. The model contains an intercept and linear term for each predictor.

2) **Pure Quadratic**
   The model contains an intercept term and linear and squared terms for each predictor.

3) **Quadratic**
   The model contains an intercept term, linear and squared terms for each predictor, and all products of pairs of distinct predictors.

4) **Interactions**
   The model contains an intercept, linear term for each predictor, and all products of pairs of distinct predictors (no squared terms as base case).

5) **Polynomial (poly*ijk*)**
   The model is a polynomial with all terms up to degree i in the first predictor, degree j in the second predictor, and so on. The maximum degree for each predictor can be specified by using a maximum polynom for each predictor. The model contains

interaction terms, but the degree of each interaction term does not exceed the maximum value of the specified degrees.

Also, variations of the above models have been used to achieve better results, i.e. even in a linear model quadratic terms for e.g. speed over ground, etc. have been introduced.

Feature Importance

F-test

The method examines the importance of each predictor individually using an F-test. An F-test compares two variances. The null-hypothesis is that the variances are equal (the features are equally important). The f-test uses different models using different number of features to deduce if the variance in the residuals are due to randomness or not. A small p-value of the test statistic indicates that the corresponding predictor is important. The output scores is – log(p). Therefore, a large score value indicates that the corresponding predictor is important. If a p-value is smaller than eps(0), then the output is Inf. The F-test used in for deriving feature importance ranks predictors in X using the response variable Y. Predictor scores, returned as a 1-by-r numeric vector, where r is the number of ranked predictors. A large score value indicates that the corresponding predictor is important. [14]

Chi-Square Test

Another variant used for the feature importance tests are based on the Chi-Squared Test. It examines whether each predictor variable is independent of a response variable by using individual chi-square tests, and then rank features using the p-values of the chi-square test statistics.

Decision Tree Model

A decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements. Decision trees are commonly used in operations research, specifically in decision analysis, to help identify a strategy most likely to reach a goal, but are also a popular tool in machine learning. [15].

The decision tree goes through recursive binary splitting. All features are considered in the start and the split that yield the lowest cost, or most information gain, are selected. For example, Gini impurity is used as a cost function. It is a measure of the likelihood of an incorrect classification. During the recursive splitting, the decrease in weighted impurity is collected and the one with the highest value are the more important feature

According to [16], decision trees are constructed using a directed graph G = (V, E), E ⊂ V2, with set of nodes V split into three disjoint sets $V = \mathcal{D} \cup \mathcal{C} \cup \mathcal{T}$ of decision, chance, and terminal nodes, respectively. For each edge e ∈ E we let e1 ∈ V denote its first element (parent node) and let e2 ∈ V denote its second element (child node). In further discussion we use the following definition: a directed graph is weakly connected if and only if it is possible to reach any node from any other by traversing edges in any direction (irrespectively of their orientation). An example of a simplified decision tree is shown below.

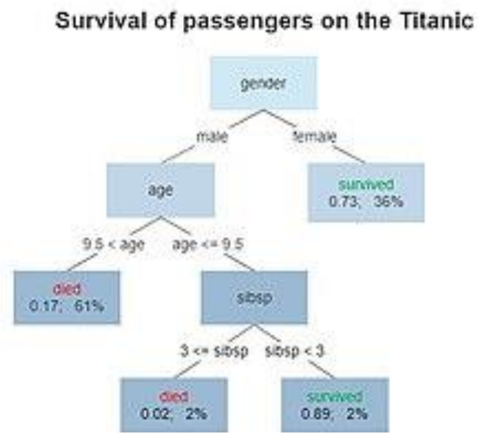


Figure 11: Decision tree example from the survival of passengers on the Titanic, source: [15]

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean/ average prediction (regression) of the individual trees. The method is used for the more advanced machine learning.

Permuted Predictor Importance

For the decision tree, a predictor importance estimates by permutation of out-of-bag predictor observations for random forest of regression trees is used.

4. Analysis and Uncertainty Assessment

4.1 Analysis of machine learning tools

For each of the machine learning models. The results are presented below for the data with all load cases and for the ballast conditions. The output is mainly presented by the standard deviation of the model error and a diagram indicating the spread of data for the model vs the real data, where the colour in the diagram represents the real fuel consumption for the specific data points.

Grey box model

The tuned hydrodynamic model fits the data reasonably well as shown in the figure below. Parameters modelled include engine, propeller characteristics, propeller load, ship resistance in different loading conditions, wind.

Some parameters are not covered by any high-quality sensor such as sea/ river current as well as the parts that are the core of the study, i.e. impact of different ballast conditions and trim. Also, variations with time and location are not covered.

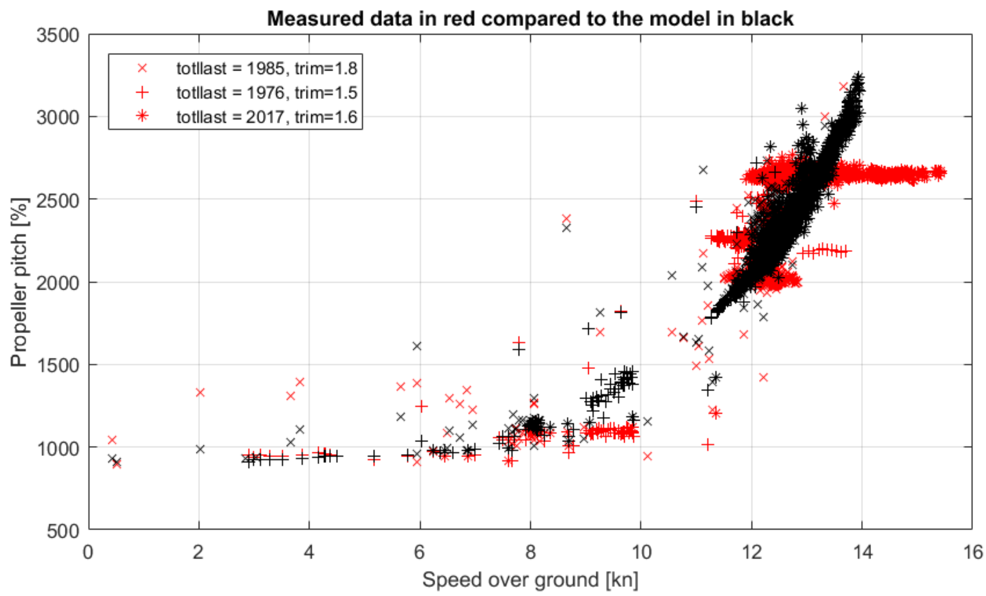


Figure 12 Speed-power prediction Comparison model vs. data

The wide spread of data shown in the grey box model indicate that certain conditions are not covered fully by the grey box model.

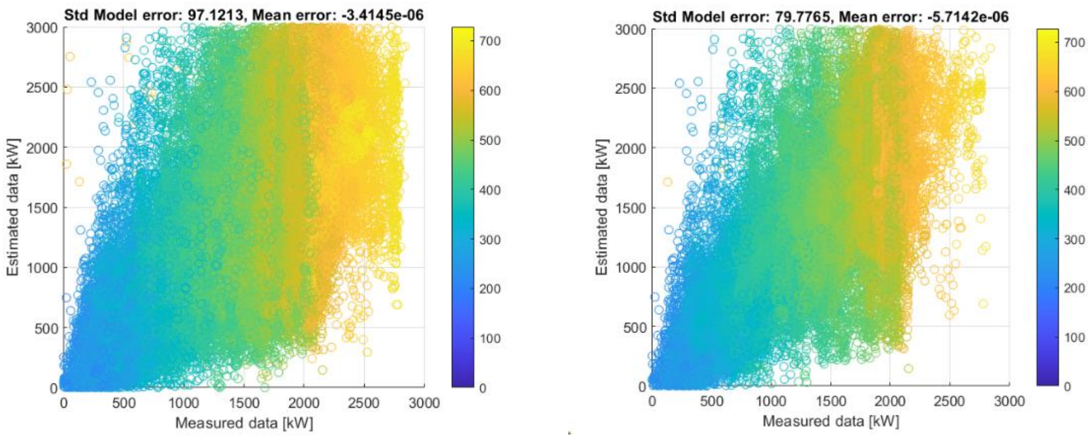


Figure 13: Grey-box model results predicting the engine load, measured vs estimated data. Left: All load cases, right: Ballast conditions. The colour represents the actual fuel consumption

Linear Regression models

The different linear regression models and feature compositions have resulted in a wide range of results. The pure linear model could be enhanced by considering more complex feature set-ups. Examples were adding of quadratic terms and multiplication of terms. The more complex feature set-ups were at the same time not always improving the results for the more advanced polynomial or interaction methods. The variation of features was based on a couple of standard sets to see the effect on accuracy. One feature set considering mainly speed related features (XSpeed), one considering dependencies from the hydrodynamic models with typical resistance and propusion equations (XDependent), one with almost all variables (XComplex) and one with the best fit (XFinal) have been used. The results from the analysis in ballast conditions are shown in the table below for the different standard deviation error.

	Xspeed	Xdependent	Xcomplex	XFinal
Linear	1.303613	0.96354	0.85648	1.221743
Pure Quadratic	1.120981	0.925754	1.920782	1.013921
Quadratic	0.906861	0.869075	0.957242	0.799801
Interactions	0.932052	0.887968	0.818694	0.818694
Polynomial	0.875373	1.0706	-	0.736825

Table 3: Results for different set ups with features against different machine learning methods, the complex model was to computationally intense to be performed.

As can be seen in the table, the more complex feature set-ups perform best with the simpler machine learning models, while they are in line or worse with the simpler feature set up. Below, the model accuracy for the different regression models is shown in its final set-up of features and labels.

1) Linear Regression

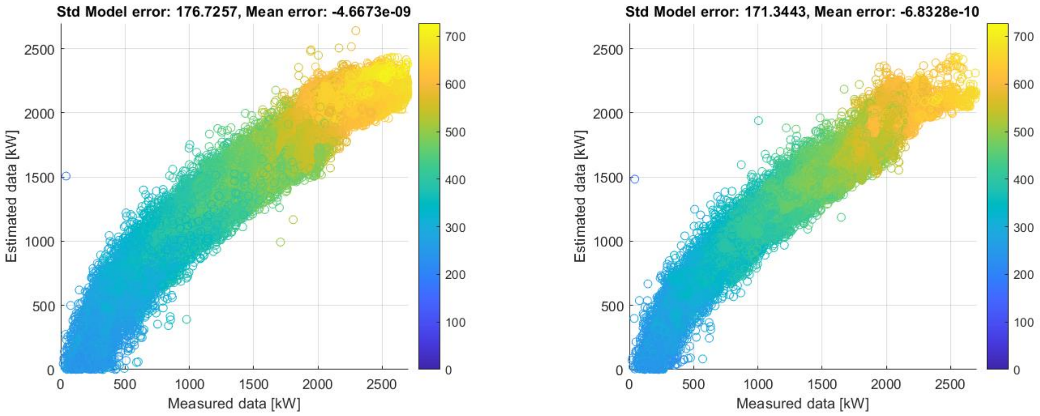


Figure 14: Results for the linear regression Model predicting the engine load, measured vs estimated data. Left: All load cases, right: Ballast conditions

2) Pure Quadratic

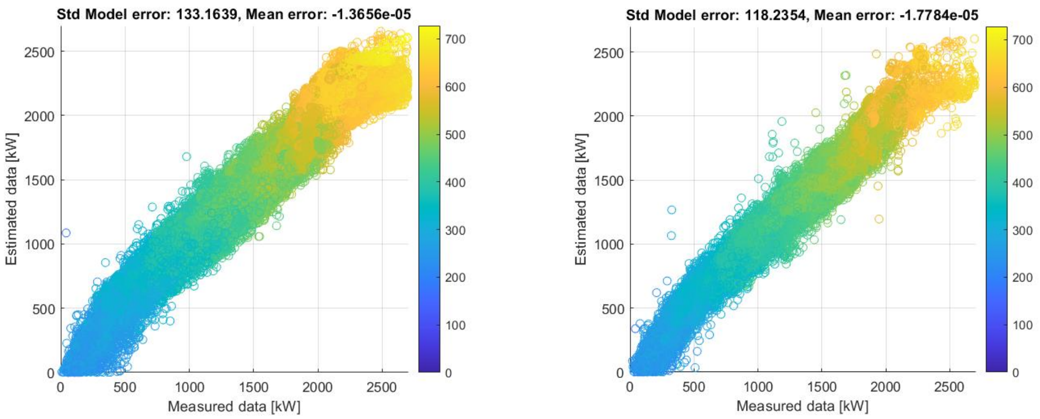


Figure 15: Results for the pure quadratic regression Model predicting the engine load, measured vs estimated data. Left: All load cases, right: Ballast conditions

3) Quadratic

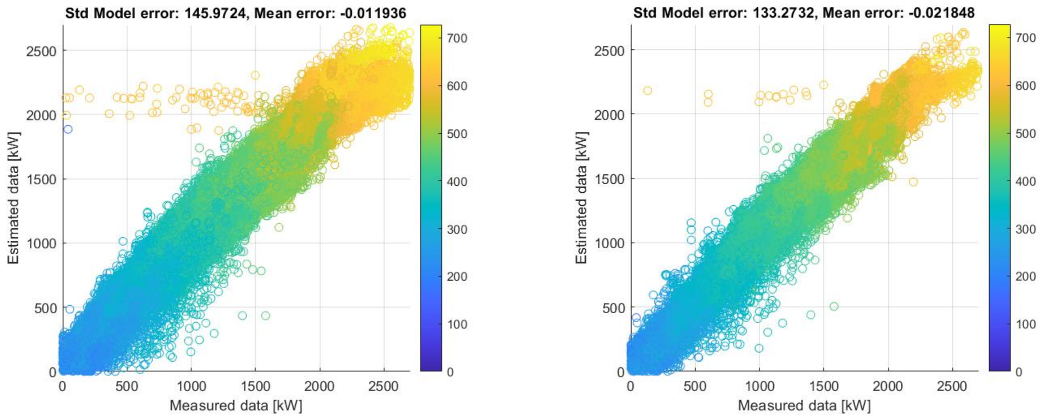


Figure 16: Results for the quadratic regression Model predicting the engine load, measured vs estimated data. Left: All load cases, right: Ballast conditions

4) Interactions

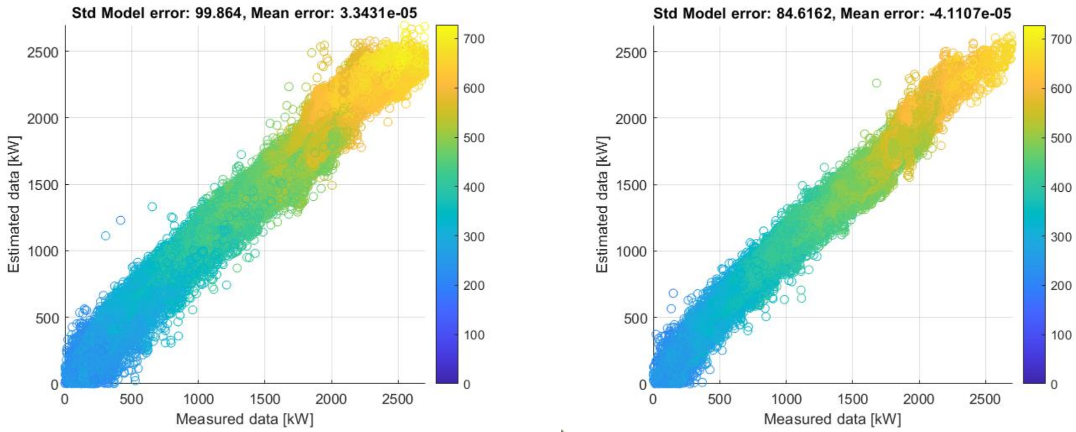


Figure 17: Results for the interaction regression Model predicting the engine load, measured vs estimated data. Left: All load cases, right: Ballast conditions

5) Polynomial (poly*ijk*)

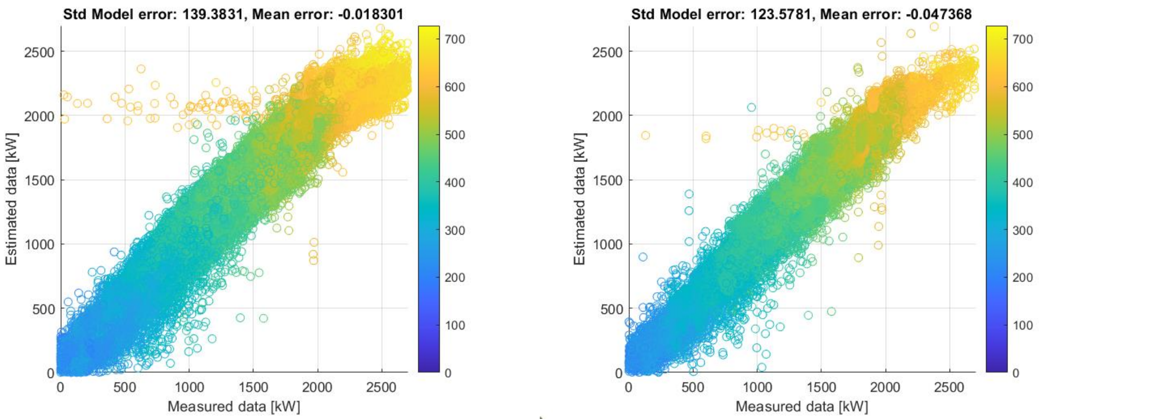


Figure 18: Results for polynomial regression Model predicting the engine load, measured vs estimated data. Left: All load cases, right: Ballast conditions

While the linear and pure quadratic models still do not seem to model the full behaviour of the vessel, the more complex models get better agreements. The final "linear" regression models used resulted in a fair prediction accuracy and was not computer intense with short learning and prediction times. The standard model errors are summarised in the table below, where it can be observed that the model for the ballast conditions are performing better than for all loading conditions.

Standard Model Error	All loading conditions	Ballast
Linear	176.72	171.34
Pure Quadratic	133.16	118.24
Quadratic	133.27	146.00
Interactions	99.86	84.62
Polynomial	139.38	123.58

Table 4: Standard model error of the various linear regression models

Feature Importance

The feature selection importance was based on the Chi-square test and on the F-test methodology. The results are presented in the figures below for all "clean" feature data, directly based on the measurements.

Chi-Square Test

The feature importance based on the Chi-squared method indicates the following parameters as dominating: Power on the shaft generator, propeller pitch, propeller RPM, time and speed over ground.

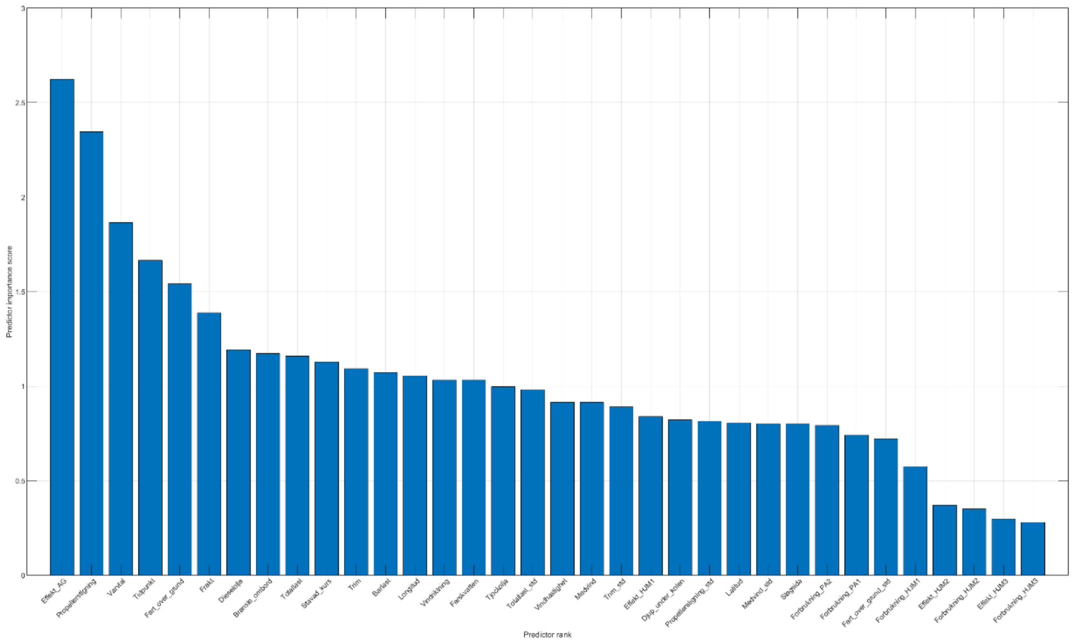


Figure 19: Feature Importance for the data set for all linear terms based on a Chi-Squared method.

F-test

The feature importance based on the Chi-squared method indicates the following parameters as dominating: speed over ground, propeller pitch, time, propeller RPM, variation in speed (accelerations) and variations in RPM.

The following interpretation for the F-test is done:

1) Accelerations and decelerations have a clear impact on consumption.
2) Most of the features identified have a direct impact on the main research question and the aim of the study.

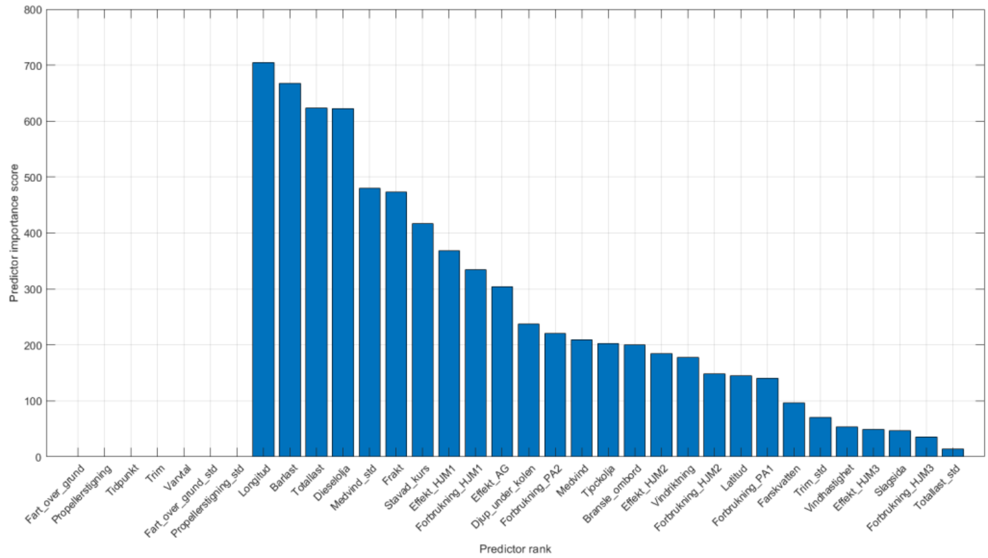


Figure 20: Feature importance for the data set for all linear terms based on an F-Test method. (Empty values on the left resulted in infinitive values during the F-test

Decision tree

The decision tree model derived indicate a very good accuracy but was the most computational intense model for training and predicting. The model fit was outstandingly best and reflects the reality with a small standard deviation.

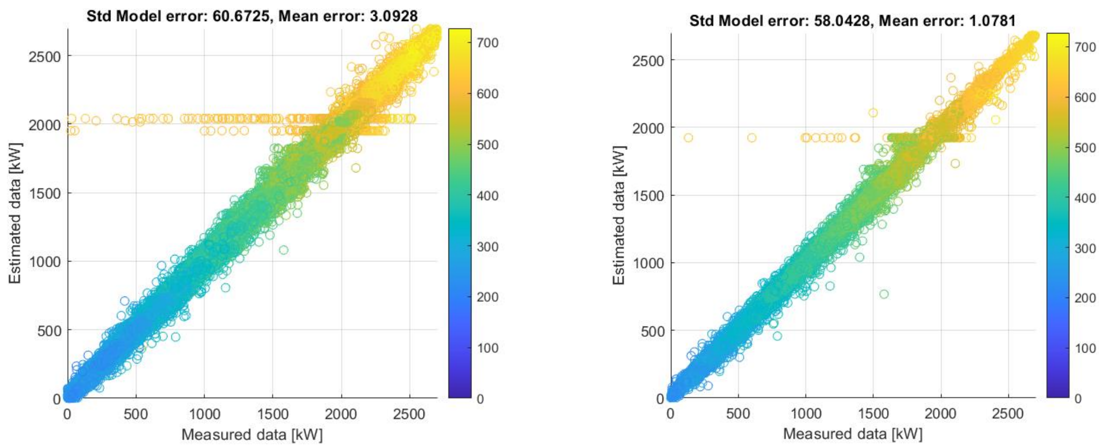


Figure 21: Results for the Decision Tree Model predicting the engine load, measured vs estimated data. The colour represents the actual fuel consumption

Permuted Predictor Importance

The predictor importance estimates by permutation of out-of-bag predictor observations for random forest of regression trees is shown below.

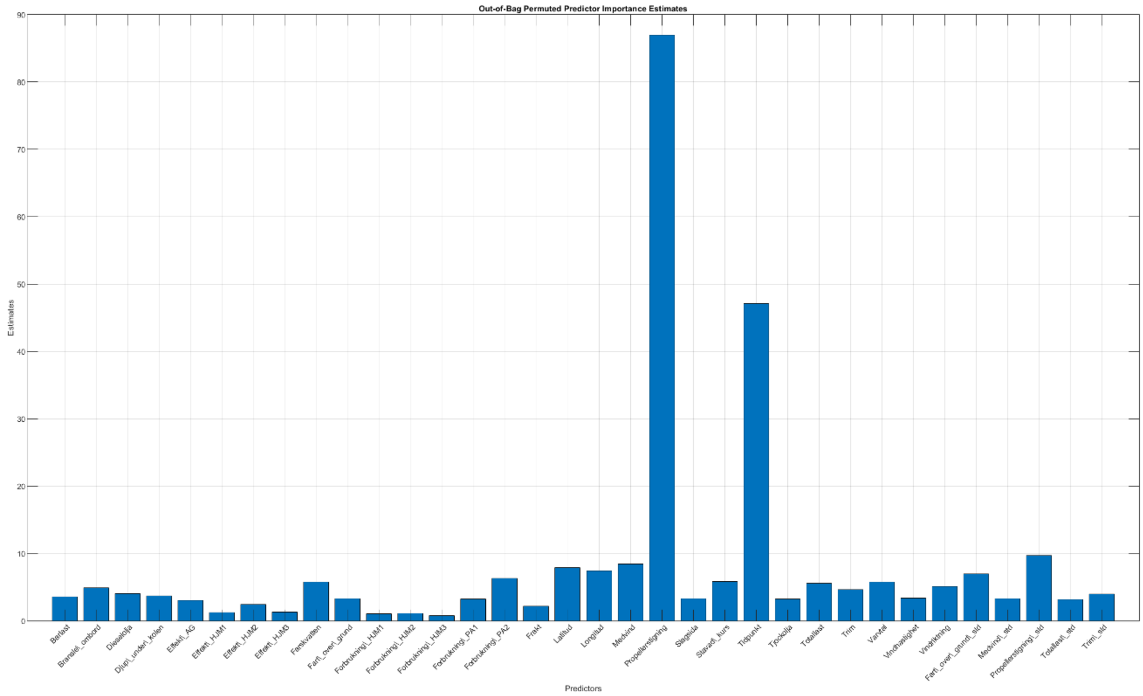


Figure 22: Permuted Predictor Importance of the different features

The permuted predictor importance indicates the following parameters as dominating: propeller pitch, time, variations in RPM, wind, position of the vessel, and variation in speed (accelerations).

The following interpretation for the F-test is done:

1) There seems to be a fluctuation of delivered power over time, which could be based on changes in the engine settings, docking and repair of the vessel, exchanges of equipment or in data collection as well as hull cleaning.
2) Most of the features identified have a direct impact on the main research question and the aim of the study.

5. Results

5.1 Optimised Trim and Ballast Conditions for the ARDEA Case – theoretical approach

The energy needed to propel a vessel is largely dependent on the total weight of it and of the speed it is operated at. Substantial savings in energy consumption and correspondingly to reduced fuel costs as well as to reduced emissions can be achieved by either lowering the speed or optimising the load taken onboard when on ballast voyages. Besides the direct savings in energy needed for pumping and treating ballast water there are indirect savings of sailing in a lighter condition with less weight onboard as the submerged area or wet surface of the vessel is smaller at lower drafts.

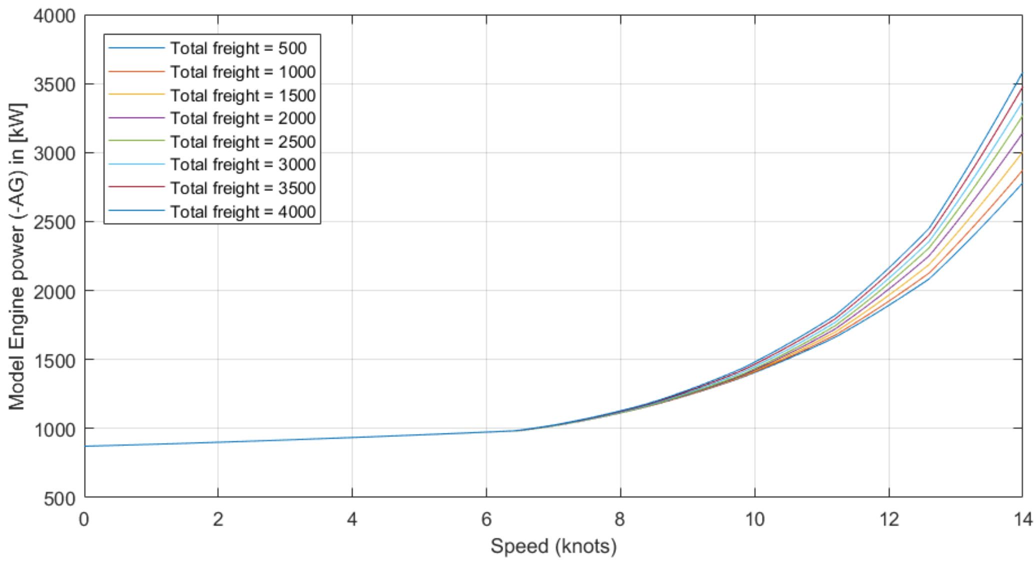


Figure 23 Speed-power chart for ARDEA at different load conditions (Total freight refers to load, incl. ballast and bunkers). Nb! The order of data plots is reverse compared to the legend order, i.e. lightest condition has lowest power requirement.

The potential of reducing fuel consumption by limiting the load onboard is shown in the chart above, where the modelled engine power is indicated for different loading conditions based on the hydrodynamic model. Typical load cases in ballast are around 2 000 ton, in loaded conditions around 4 000 ton.

5.2 Ballast Conditions Tests

The average and median loading conditions in ballast are around 1800 tons, this results in a total load of 2083 tons total load (freshwater, fuel, etc.). Trim is typically 1.74m in ballast conditions.

As the decision tree model has performed best, it is used for the prediction of fuel savings achieved in summer ballast conditions. To allow for a suitable comparison that is fair, the same conditions are predicted by the model for the average ballast conditions.

Four different trials have been performed with summer ballast conditions. The details are given in the tables below:

M/T A RDEA BALLAST CONDITION	**1425 TON**	**1525 TON**	**1625 TON**	**1725 TON**
VOY. NR.	38/20	45/20	39/20	44/20
BUNKER/FW ON S.O.S.P (DEPARTURE)	213.6 / 60 ton	97.6 / 58 ton	197.4 / 55 ton	160.8 / 54 ton
BUNKER/FW ON E.O.S.P (ARRIVAL)	209.8 / 58.8 ton	81.6 / 57 ton	193.5 / 53 ton	135.5 / 45.4 ton
PITCH (PROPELLER)	8, 5, 4	8	8	8

Table 5: Conditions at four trails regarding amount of ballast water, bunkers and fresh water onboard at start of sea passage and at end of sea passage. Pitch of the propeller is indication of power management.

BALLAST INTAKE TON	**S.O.S.P DATE/TIME**	**DRAFT F/A**	**E.O.S.P DATE/TIME**	**DRAFT F/A**	**WEATHER CONDITION**
1425	24.06.2020/23:40	3.5/5.0 m	25.06.2020/08:20	3.5/5.0 m	Calm sea
1525	01.08.2020/02:20	3.6/5.2 m	02.08.2020/07:55	3.6/5.1 m	slight
1625	27.06.2020/14:00	3.8/5.3 m	27.06.2020/21:15	3.8/5.3 m	slight
1725	24.07.2020/22:40	3.6/5.5 m	26.07.2020/21:10	3.6/5.4 m	Sea moderate, SE 6/4

Table 6: Details on the four trips during trials. Conditions at departure (S.O.S.P) and arrival (E.O.S.P) and observed weather conditions.

The charts below show the measured and modelled power requirements at average ballast and at summer ballast conditions and the expected energy savings for the various trips at different speeds.

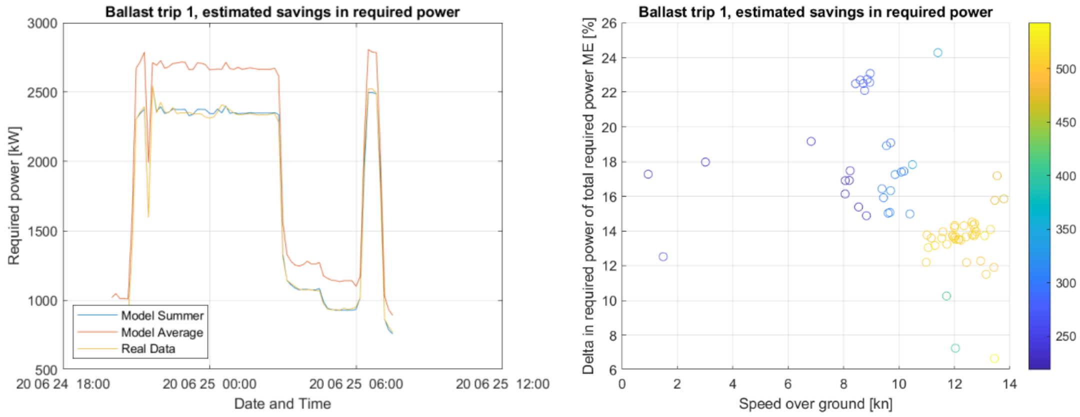


Figure 24 Trail 1, abt. 1500 ton total load and 1.5 m trim. Required power modelled at summer and average ballast condition vs measured data. 2nd chart shows Estimated savings in power need at different speeds. Colour of data point indicates fuel consumption.

The first trip studied is a short trip in light ballast and in calm seas. It shows a good match between modelled and measured data. Savings in required power are about 14% at 12 kts speed.

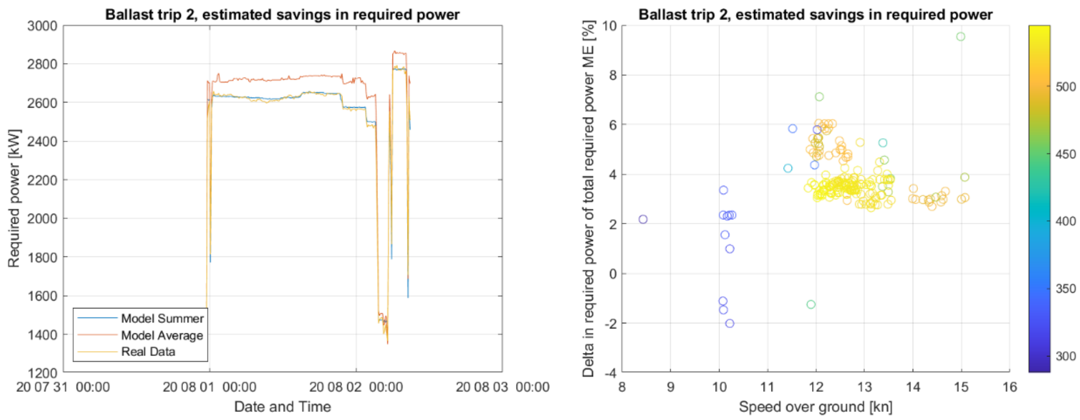


Figure 25 Trail 2, abt. 1670 ton total load and 1.6 m trim. Required power modelled at summer and average ballast condition vs measured data. 2nd chart shows Estimated savings in power need at different speeds. Colour of data point indicates fuel consumption.

The second trip is a longer trip, some 24 hrs, with slight wind conditions. It also shows good consistency with modelled values. The power reduction is only some 3,5 – 6 % in the 12-13 kts speed range.

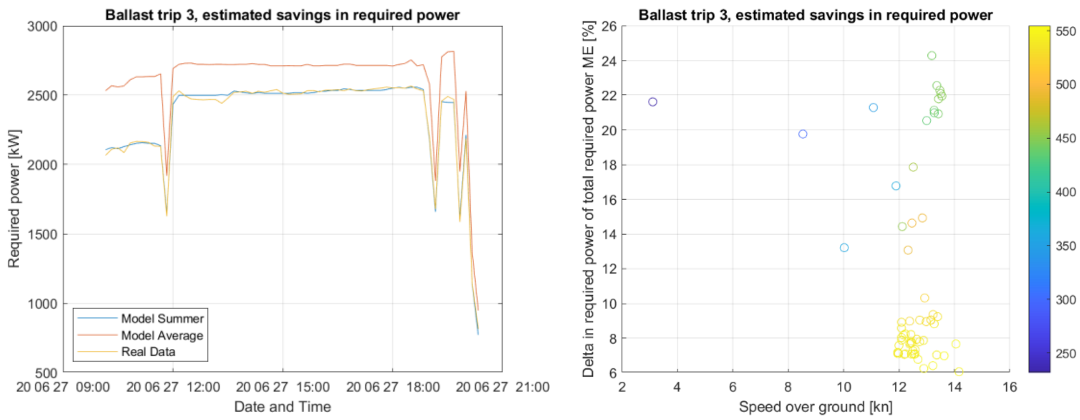


Figure 26 Trail 3, abt. 1870 ton total load and 1.5 m trim. Required power modelled at summer and average ballast condition vs measured data. 2nd chart shows Estimated savings in power need at different speeds. Colour of data point indicates fuel consumption.

Third trip studied is a short trip with slight wind observed. The savings compared to average ballast conditions are 7-9% at abt. 12 kts speed.

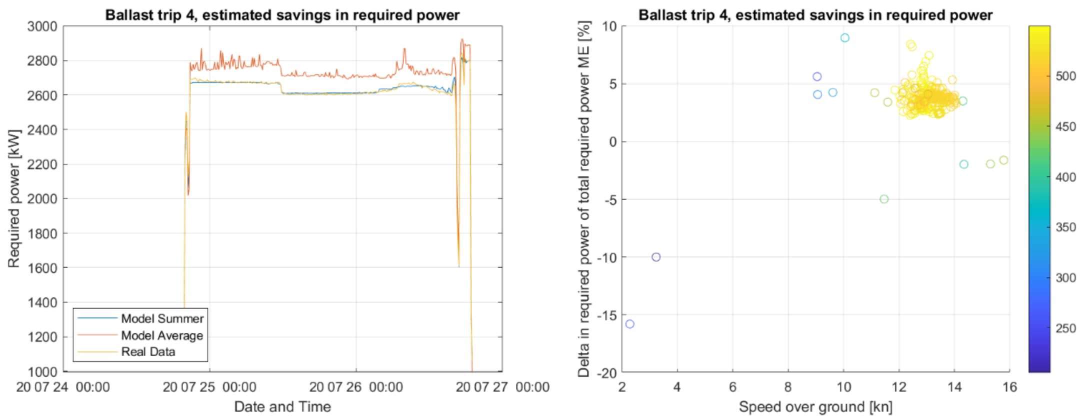


Figure 27 Trail 4, abt. 1920 ton total load and 1.9 m trim. Required power modelled at summer and average ballast condition vs measured data. 2nd chart shows Estimated savings in power need at different speeds. Colour of data point indicates fuel consumption.

The fourth trip is a longer voyage (48hrs) with a higher total load and moderate wind conditions observed. The reduced resistance results in lower power needs of abt. 4-5% at 12-14 kts.

The savings are when sailing at 12 kts are summarised in the table below and related to observed wind conditions and total load onboard.

Table 7 Savings in required power when sailing at 12 kts in different load and weather conditions.

VOY. NR.	38/20	45/20	39/20	44/20
TOTAL LOAD (APPROX.)	1500 ton	1670 ton	1870 ton	1920 ton
WIND CONDITION	Calm	Slight	Slight	Moderate
SAVINGS AT 12 KTS	14%	3,5-6%	7-9%	4-5%

The reduction in resistance and power needed to propel the vessel at 12 kts seems to be highest at light load conditions and in calm weather, which corresponds well with sound naval architectural theories.

5.3 Potential for "static" Energy Savings

Reduced use of unnecessary ballast water onboard is beneficial as it reduces the energy consumption in several ways, both directly and indirectly, while at sea as well as before and after voyages during the ballasting operations:

1. First it reduces the amount of water that is pumped in and out of the ballast water tanks. Less run time on pumps and less energy needed to run them. This also requires less maintenance and lowers the costs.
2. Less water being pumped reduces the need for treatment of ballast water as per the Ballast Water Treatment requirements. Less treatment requires less energy and less maintenance costs.
3. Less ballast water onboard reduces the mass of the vessel and thus the inertia and total mass to be propelled through water. Less mass requires less energy needed for propulsion.
4. Less mass onboard will result in the vessel laying higher in the water (or decrease the draught of the vessel) which reduces the body under the waterline and wet area which lowers the resistance. Less resistance translates to less energy needed to propel the vessel forward at desired speed.

Table 8 Savings in ballast water pumping and treatment when sailing in lighter ballast conditions. Pump time, Energy and fuel saving have been doubled as ballast water is pumped both in and out.

VOY. NR.	38/20	45/20	39/20	44/20
BALLAST CONDITION	1425	1525	1625	1725
DELTA BALLAST WATER INTAKE (TON)	375	275	175	75
PUMP TIME SAVED (HRS)	1,88	1,38	0,88	0,38
ENERGY SAVED (KWH) INTAKE AND OUT	351	257	164	70
MDO SAVED (KG)	70	51	33	14

5.4 Effect of docking

The vessel has been dry-docked and the hull has been cleaned in late February 2020. As part of the evaluation, the derived model is used to magnify the savings based on a clean hull compared to a hull with fouling (marine growth). The approach here differs from the one described above, as shown in the figure below:

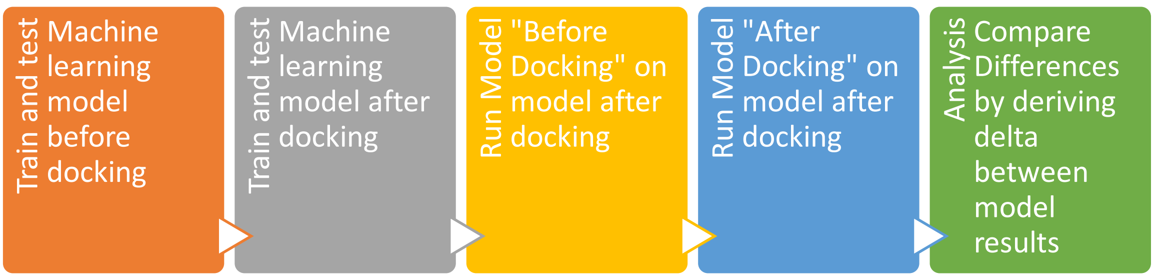


Figure 28: Approach for optimised ballast conditions analysis and savings

The graphs below compare the modelled required power in kW before and after hull cleaning and actual data measurements after the dry-docking. The first chart (Figure 29) shows the first weeks following the dry-docking, while the second charts shows effect in June, four months later (Figure 30). The savings start at above 10%, but decrease quickly over time, which is expected when the fouling picks up again. The marine growth is especially significant during the warmer summer months.

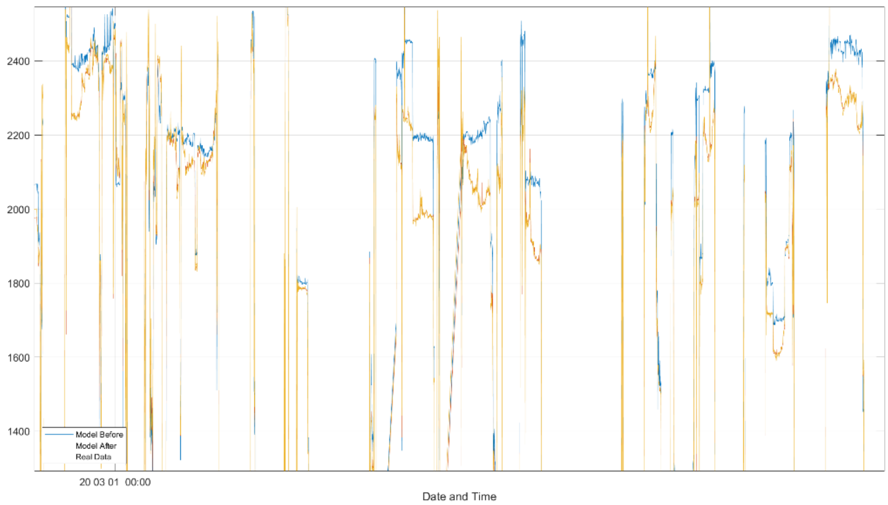
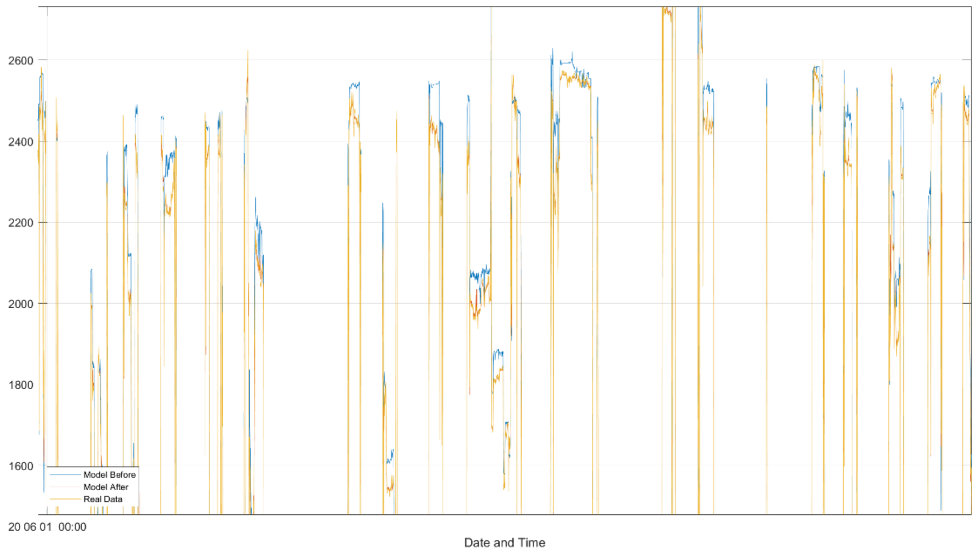


Figure 29: First weeks after dry-docking. Comparison of modelled Required power before (blue) and after (red) dry-docking, the real data points (yellow) correspond very well with model. The difference is significant between the clean hull and the fouled with savings over 10% initially.



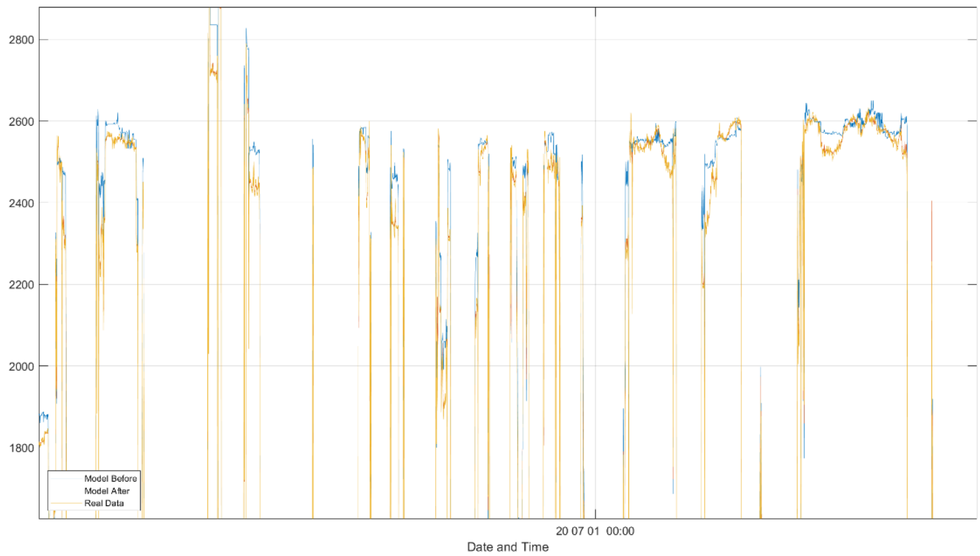


Figure 30: Summer period (June). Modelled required power before and after the dry-docking in February. The difference is approx. 5% at start of June but is almost negligible at the end of the period.

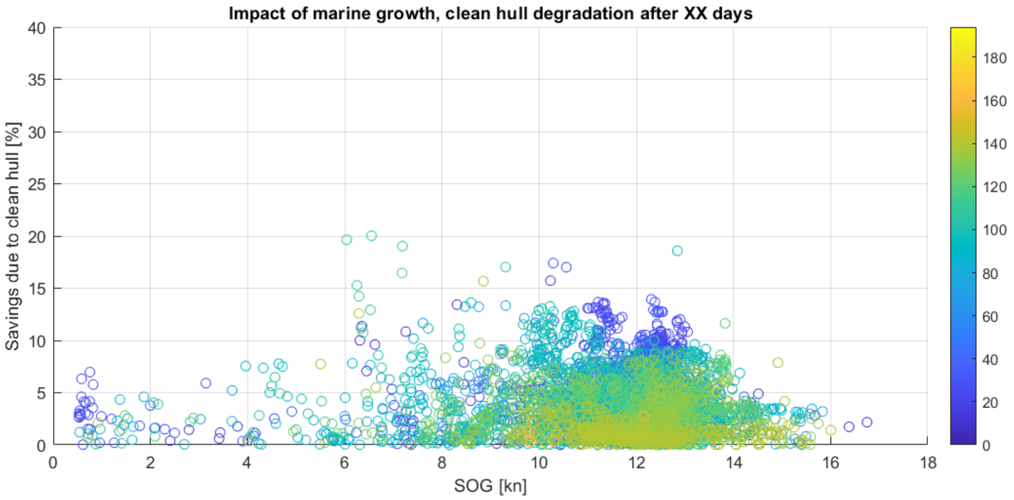


Figure 31 Impact of marine growth on the hull over 180 days. Colour scale indicates days passed following hull cleaning. 10-14% saving first months, diagram based on engine delivered power.

The newly cleaned hull requires significantly less power to sail at 12 kts than with extensive fouling. In the case studied above the effect is profound during the first months but decreases over time when the sea water temperature rises, as can be seen in Figure 23 above.

6. Recommendations and Guidelines

6.1 Conclusions from this Study

This study has derived some general results, which can be relevant for other ship owners as well and are therefore part of the recommendations.

A small bitumen tanker such as ARDEA has few ballast tanks and more limited possibilities to adjust its trim. With a vessel that has more ballast water tanks, the possibility to systematically vary trim conditions to reduce fuel consumptions could result in even higher savings.

Savings with reduced ballast do not only have an impact as savings when under way, but also lead to a reduced need for pumping of water into and out of the ballast tanks and for ballast water treatment plants both of which are energy consuming. Energy savings translate to positive reductions of both cost for fuel and in amount of emissions such as CO_2 and other GHG. Further strengthening the business case is the benefits of reduce load and run time on ballast water pumps and on the ballast water treatment system which reduces the costs for the upkeep of the vessel.

Data and model conclusions:

- The approach can be applied directly to other vessels if data are available
- The model is fit for desired purpose and savings can be quantified with regards to ballast water intake optimisation
- Trim optimisation represents a harder challenge based on the data provided, but certain conclusions can be drawn
- Certain parameters have not been included as intended, as they are either not available or are harder to model (wave and current)
- Even simpler models with low computational needs can give significant support which allows simple implementation.
- There is a large potential for decision support to aid ship managers in processing data and drawing the right conclusions to unlock additional savings in energy usage.
- There are many applications of this data, also tank heating, marine growth, etc., could be optimised based on the data collected.

Benefits identified:

- Reduction in resistance leads to reduced power needed in light/ summer ballast conditions.
    - Summer ballast implies a reduction in fuel consumption in the range of 5-15% on the feasible trips. Largest savings in lighter load conditions and calm weather.
- Reduced run-hours of ballast water treatment equipment and pumps
- Reduced power consumption of this auxiliary equipment
- The benefit of collecting and processing operational and voyage data has large potential for quick pay-back on time and resources invested.
- Significant interest of the ship-owner involved, and of others, to make use of results

Observations from other data extracted from Energy Management system

- Heating of load strongly dependent on outside temperature → potential for reduction
- Effect of docking of the ship and cleaning of hull visible in data (>10% on power needed) -> Indicator for crew and management to plan hull cleaning.

6.2 Recommendations regarding Machine Learning Tools

Based on the experience from building models and machine learning algorithms obtained in this study it is concluded that many times it is recommended to use simple and robust models such as decision tree random forest or variations of linear regressions. Grey box models are more complex to be implemented but might give faster results (shorter data collection period). A grey box model is not needed for all purposes.

The accuracy is considered enough for most applications.

The value of reliable, high resolution data and data processing is substantial. The methodology used in this study can be applied also in other settings and for other data processing.

6.3 Guidelines for Improved Energy-Efficiency based on Collected Data

1. Recommendation for improved decision support tools based on data analysis
    a. Recommendations on further data to be included in energy saving management systems (such as currents, etc.)
    b. Recommendations on how to integrate energy management systems with load computer systems' optimisation of ballast/trim/list for best fuel consumption.
    c. Guideline for improved vessel efficiency through big data analysis including (quantitative) estimate of eco-efficiency benefits from use of digital data and machine learning methods, decisions support tools
2. Recommendations for Operational procedures for increased energy efficiency
    a. Educate the crew and management in best practices and encourage crew to adopt an active approach to operational energy optimisation, such as
        i. minimising ballast water intake when sailing in favourable conditions
        ii. adjusting trim to more favourable conditions
        iii. clean hull when possible - make use of off-hire opportunities due to seasonal variations in cargo lows
        iv. Eco-steaming when sailing in ballast condition / out-of-charter
    b. With good quality live stream data on ship performance and conditions together with adequate decision support readily available to the crew they can actively adjust parameters to optimise for each voyage and operation.
    c. Encourage crew to share experiences on energy optimisation between themselves and with the rest of fleet.
    d. Adopt machine learning tools that can canvas through historical data and predict the outcome for different actions

6.4 Next Steps

To penetrate more deeply into the findings of this study it is recommended that future studies should be made to:

- Measure the specific energy needed for cargo tank heating for individual tanks to study impact of Cargo tank insulation.
- As ARDEA has somewhat limited flexibility compared to a traditional product/Chemical tanker it is suggested that such vessels be studied as well. They should have a greater potential to elaborate with variations in trim, ballast conditions. This should be given priority.

- Due to COVID-19 effects there was a limited possibility to test and verify the outcome and it is desirable that the outcome be further verified by additional trails in summer ballast conditions.
- Further investigate the use of machine learning tools to predict the effects of fouling in order to help ship management to decide when hull cleaning would be most beneficial.
- Investigate the possibilities for an artificial notice of readiness it would allow for larger flexibility in adjusting actual arrival if the quay is occupied or other matters force the vessel to lay-by. Presently the contracts used do not support digital N.O.R, even though BIMCO has worked on such clauses.

In order to take the results onward and come to benefit for other ship owners and operators more extensive guidelines and best practices should be compiled and disseminated.

References

[1] J. Hüffmeier, "State-of-the-Art Energy Efficiency of Ships," RISE Research Institutes of Sweden, Gothenburg, 2020.

[2] ABS, "Ship Energy Efficiency Measures - Status and Guidance," American Bureau of Shipping, Houston.

[3] A. M. &. N. L. M. Reichel, "Trim Optimisation - Theory and Practice," *TransNav the International Journal on Marine Navigation and Safety of Sea Transportation,* vol. 8, no. 3, pp. 387-392, 2014.

[4] M. Boytim, "Trim Optimisation - Sustainable savings," *SSPA Highlights,* pp. 2-3, 2009.

[5] T. D. a. E. A. &. F. Rederi, Interviewee, [Interview]. 20 January 2020.

[6] IMO, *Fourth IMO GHG Study 2020 – Final report,* London: International Maritime Organisation, 2020.

[7] T. S. C. C. S. M. Michael Persson, Interviewee, *Email: EcoProDigi - User case Ardea.* [Interview]. 02 July 2020.

[8] "Technical details Model G6300 Marine Diesel Engine," Weizhu, [Online]. Available: http://www.weizhou.com.tw/Agrimachine/DieselEngine/Web/Marine-engine/G6300.htm. [Accessed 15 october 2020].

[9] FKAB, "Frederiet Ardea & Mergus - 4700 DWT Bitumen Carrier," [Online]. Available: https://www.fkab.com/wp-content/uploads/sites/3/Ardea-Mergus-LOW.pdf. [Accessed November 2019].

[10] T. A. Tran, "Calculation and Assessing the EEDI Index in the Field of Ship Energy," *Journal of Marine Science: Research & Development,* vol. 6, no. 6, pp. 1-6, 2016.

[11] IMO, *MEPC.308(73) - 2018 Guidelines on the Method of Calculation of the Attained Energy Efficiency Design Index (EEDI) for New Ships,* London: International Maritime Organisation, 2018.

[12] Dannish Shipping, "Calculation tool for assessment of ships' energy consumption and fuel gas emissions, including CO_2_ (EEDI)," 15 February 2015. [Online]. Available: https://www.danishshipping.dk/en/policy/klimapolitik/beregningsvaerktoejer/. [Accessed 27 Oktober 2020].

[13] U. M. Fayyad, G. Piatetsky-Shapiro and P. Smyth, “From Data Mining to Knowledge Discovery: An Overview,” in *Advances in Knowledge Discovery in Databases*, AAAI/ MIT Press, 1996, pp. 1-34.

[14] C. E. R. M. N. G. E. H. Rasmussen, D. v. Camp, M. Revow, Z. Ghahramani, R. Kustra and R. Tibshirani, *The DELVE Manual,* Cambridge Machine Learning Group, 1996.

[15] Wikipedia, *Decision tree,* Wikipedia, 2020.

[16] B. Kamiński, M. Jakubczyk and P. Szufel, “A framework for sensitivity analysis of decision trees,” *Cent Eur J Oper Res (26) 1,* p. 135–159., 2018.