A DATA DRIVEN APPROACH FOR SHIP ENERGY EFFICIENCY AND MAINTENANCE

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ABSTRACT
The challenge of maintaining human activities and development while reducing their impact on the environment, and particularly in the climate, has become relevant also for shipping in the latest years. Similarly, to other sectors, the shipping industry is being asked to become more and more sustainable, and hence to reduce its emissions of greenhouse gases. Many shipping companies started to collect large databases of measured environmental and operational data to be used as sources of information for improving ship's performance. However, the extraction of useful information from large datasets of mixed quality is not a trivial task that requires advanced knowledge at the intersection of computer science and marine engineering. In this paper, the authors present a machine learning-based approach to analyse large databases of ship operational data and to use them for the reduction of fuel consumption and carbon emissions. Based on the available historical data and technical information of the ship, the authors derived a Machine Learning technique for the estimation of the degradation of ship performance over time, and to the evaluation of the effectiveness of maintenance activities such as hull and propeller cleaning.

Keywords: Data driven models, hull and propeller cleaning, maintenance, ship performance

1. INTRODUCTION

The challenge of maintaining human activities and development while reducing their impact on the environment, and particularly in the climate, has become relevant also for shipping in the latest years. Similarly to other sectors, the shipping industry is being asked to become more and more sustainable, and hence to reduce its emissions of greenhouse gases (Winnes et al., 2015; Nikolakaki, 2013; Smith et al., 2014). Many shipping companies started collecting large databases of measured environmental and operational data to be used as sources of information for improving ship's performance (Coraddu et al., 2017; Kakuta, 2017). The expectations from these efforts in data collection are high: not only should it be possible to estimate the vessel's performance, its deterioration over time and the effect of maintenance operations, such as dry-docking or hull cleaning, but they should also allow ship owners to estimate the savings generated from energy-savings technologies.

There are many ship and environmental factors that influence the performance of a vessel in operations. Table 1 and Table *2* summarise the most relevant ones. Among the ship factors, the hull and propeller condition play a pivotal role in ship efficiency (Schultz, 2007; Atlar et al. 2002).

Biofouling affects the hydrodynamics of the hull by increasing drag causing drag related speed loss and increases fuel consumption to maintain the service speeds (Candries er al., 2003). The effect of slime, alone, impacts ship performance up to 19% as reported in Table 3. This effect is caused by the viscous resistance increase with the roughness of the hull surface. Nevertheless, the assessment of the friction drag from surfaces with different types and shapes of roughness is still one of the major questions in fluid mechanics (Demirel, et al., 2017).

As reported in (Haslbeck, 2003), the increase in fuel consumption caused by the propeller fouling range from 6% to 14%. Accretions of marine organisms cause an increase in the roughness of the blade surface, and this is the primary cause of marine propeller performance degradation (Khor & Xiao, 2011). Hull and propeller fouling are the main causes of increased fuel consumption and the corresponding increases in GHG emissions vessels (Buhaug, 2005).

Table 1: Operational factors

Ship Factors
Draft
Trim
Rudder activity
Hull condition
Propeller condition
Fuel quality
Drift

Table 2: Environmental factors

Environmental Factors
Wind and Waves
Sea currents
Water depth, density and viscosity

Water temperature	Air barometric pressure
Air humidity and temperature	

The lost energy due to fouling-related losses can be relevant as reported in Table 3. However, the assessment of this effect is not a trivial task since the operational and environmental conditions of the vessel are responsible for high variability in performance. As the roughness of micro fouling and macro fouling cannot be estimated in operations, an advanced and accurate performance monitoring systems could provide a prediction on when to clean the hull for cost optimisation and reduction. A real-time vessel performance assessment model could provide to the ship owner a better understanding of the need to clean the hull or dry docking.

Table 3: Influence of Hull and Propeller Condition (Schultz, 2007)

Visual Hull Condition	Power increase [%]
Freshly Applied Hull Coating	0
Deteriorated Coating or Slime	9
Heavy Slime	19
Small Calcareous Fouling or Macroalgae	33
Medium Calcareous Fouling	84

Today’s industrial reference for ship performance monitoring is set by the ISO standards (BSI, 2015; BSI, 2016). According to the procedures suggested by the ISO, the actual measurements of ship power and speed are corrected for actual ship trim and displacement based on water tank tests, and for the influence of wind and waves based on semi-empirical formulations. The comparison between the theoretical expected speed and the measured provides an estimation of the ship added resistance related to fouling.
Although this method has proven to be rather effective in its practical implementation, it should be noted that it does not allow to differentiate the contribution of machinery degradation to the degradation of hull and propeller, and only partly accounts for the influence of winds and waves.
The relevant literature about hull condition monitoring (Logan, 2012), considers the effects of current, ship motions, rudder, and transients applying filters to exclude from the analysis data containing these effects. In this paper, the authors present a machine learning-based approach to analyse large databases of ship operational data and to use them for the reduction of fuel consumption, carbon emissions and the improvement of maintenance activities.
The approach proposed in this paper, differently from industry standards and the existing literature on the subject, takes advantage of all the data collected while the vessel is in operation without applying any filtering. The extraction of useful information from large and heterogeneous datasets is not a trivial task, and it requires advanced knowledge at the intersection of computer science and marine engineering. Onboard measurement systems rarely measure the values that are needed and are subject to inaccuracies and bias. Moreover, one of the main challenges is related to the sensors’ precision installed onboard. For instance, the speed logs have an error band in their speed measurement as great as the speed loss that can be induced by hull and propeller condition.
For these reasons, the authors exploited a data analytics approach based on one of the state-of-the-art Machine Learning (ML) algorithms. In particular, the Deep Extreme Learning Machines (DELM) (Oneto et al., 2017) algorithm has been utilised as it can deal the raw and heterogeneous data and find a good representation of it by filtering the noise. Moreover, as reported in (Tang et al., 2015), DELM can extract the most suitable model of the phenomena under exam.

2. VESSEL DESCRIPTION

2.1 PROPULSION PLANT

The methods proposed in this paper for the estimation of changes in ship performance are applied to a case study. This ship is a Handymax chemical/product tanker propelled by two main engines (MaK 8M32C four-stroke Diesel engines) rated 3840 kW each and designed for operation at 600 rpm. The engines are connected to a gearbox that distributes the power output between the controllable pitch propeller for propulsion and a shaft generator (rated 3200 kW). Two auxiliary engines rated 682 kW each, can also generate auxiliary power. Both the main engines are provided with an exhaust gas boiler, that can be integrated by two auxiliary oil-fired boilers. A conceptual representation of the ship propulsion plant is shown in Figure 1, while main particulars of the vessel are presented in Table 4.
The ship mainly operates according to a variable schedule, both regarding time spent at sea and of ports visited. Based on the market requirements, the vessel operates over a wide range of operational and

environmental conditions, thus making it hard to estimate small variations in ship performance. In Figure 2 examples of the operational condition regarding ship speed (a) and trim (b) are reported. While in Figure 3 examples of the environmental condition regarding wind speed (a) and direction (b) are depicted.

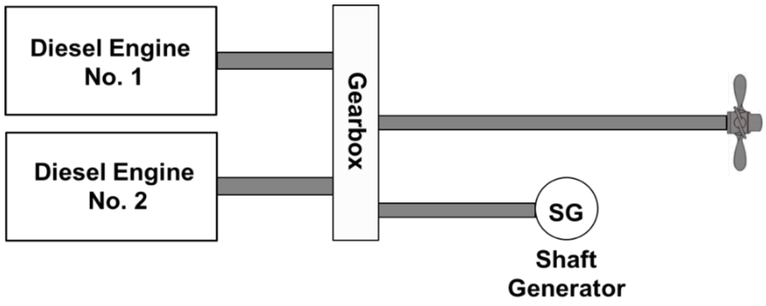
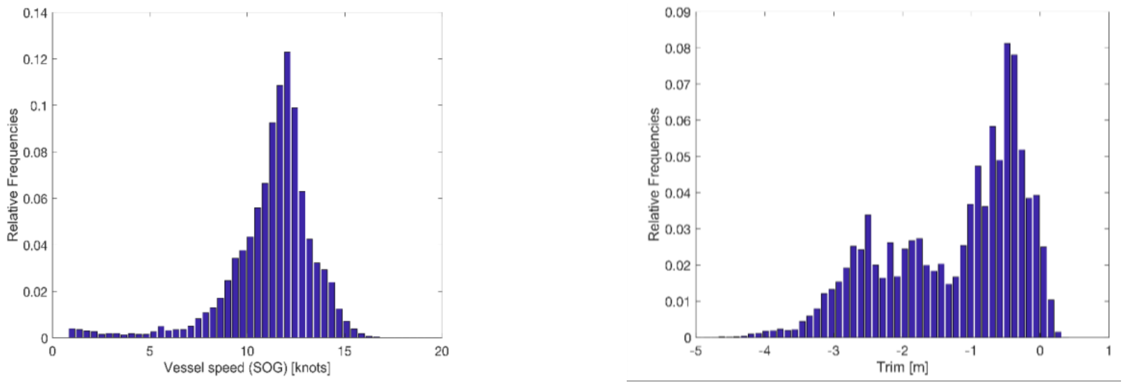


Figure 1: Conceptual representation of the ship propulsion system

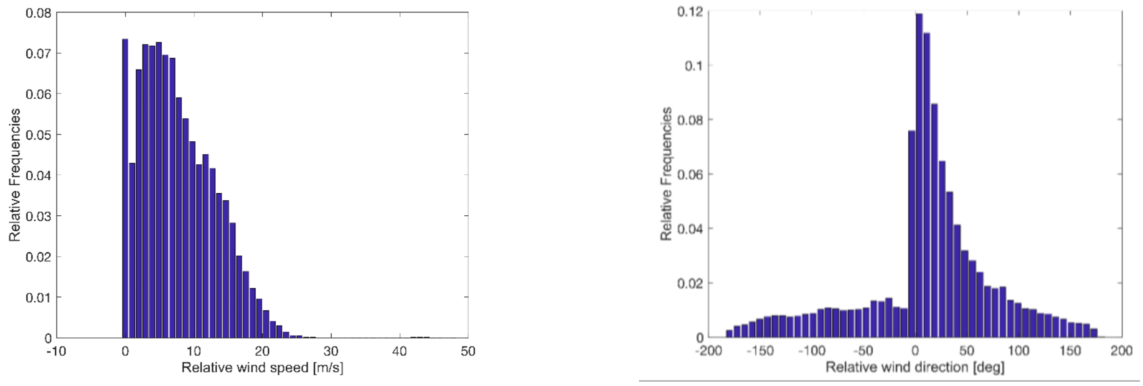
Table 4: Main features of the case study ship

Ship feature	Value	Unit
Deadweight	47000	[t]
Installed power (Main Engines)	3840 (x2)	[kW]
Installed power (Auxiliary Engines)	682 (x2)	[kW]
Shaft generator power	3200	[kg/h]
Exhaust boilers steam generators	1400	[kg/h]
Auxiliary boilers steam generators	28000	[kg/h]



(a) (b)

Figure 2: Speed over ground (a) and trim (b) relative frequencies during the observed period



(a) (b)

Figure 3: Relative wind speed (a) and direction (b) relative frequencies during the observed period

2.2 DATA LOGGING SYSTEM

The vessel is provided with a data logging system which is used by the company both for on board monitoring and for land-based performance control. Table 5 summarises the available measurements from the continuous monitoring system. The original data frequency measured by the monitoring system is of 1 point every 15 seconds. To provide easier data handling, the raw data are sent to the provider server, where they are processed into 15 minutes averages.

Table 5: Measured values available from the continuous monitoring system

Variable name	**Unit**	**Variable name**	**Unit**
Time stamp	[t]	Sea depth	[m]
Latitude	[°]	Sea Water Temperature	[°C]
Longitude	[°]	CPP Set point	[°]
Main engines fuel consumption	[kg/h]	CPP Feedback	[°]
Auxiliary engines power output	[kg/h]	Fuel Density	[kg/m^3]
Shaft generator power	[kg/h]	Fuel Temperature	[°C]
Propeller shaft power	[kW]	Ambient Pressure	[bar]
Propeller speed	[rpm]	Relative Humidity	[%]
Ship draft (fore)	[m]	Dew Point Temperature	[°C]
Ship draft (aft)	[m]	Shaft Torque	[kN m]
Draft Port	[m]	Rudder Angle	[°]
Draft Starboard	[m]	Acceleration x Direction	[m/s^2]
Relative wind speed	[m/s]	Acceleration y Direction	[m/s^2]
Relative wind direction	[°]	Acceleration z Direction	[m/s^2]
GPS heading	[°]	Roll	[°]
Speed over ground	[knots]	Pitch	[°]
Speed through water	[knots]	Yaw	[°]

3. VESSEL PERFORMANCE PREDICTION

This section deals with the problem of building a data-driven model able to integrate the heterogeneous data, as reported in Table 5, for the vessel's performance prediction and performance degradation. To reach this goal, based on the available historical data the author proposed an innovative approach based on a two-step data analytics ML techniques which exploit a state of the art tools and the knowledge of physical problem so to identify the performance degradation. The proposed approach consists of two phases depicted in Figure 4.
In Phase I, part of the historical data has been used from to build the predictive model of the fuel consumption. In particular, the first two months of navigation after the main dry-dock has been used. Given the data observations during the clean hull and propeller operational condition, the performance prediction problem has been mapped into a classical multivariate regression problem (Vapnik, 1995).
In the regression framework (Shawe-Taylor & Cristianini, 2004) a set of data $D_n = \{(x_1, y_1), \dots, (x_n, y_n)\}$ with $x_i \in X \in R^d$ and $y_i \in Y \in R$, are available from the vessel data logging system. The goal is to identify the unknown model $S: X \to Y$ through a model $M: X \to Y$ chosen by an algorithm A_H defined by its set of hyperparameters H.
The accuracy of the model M in representing the unknown system S has been evaluated with reference to the mean square error (MSE) and the model selection phase has been carried out via bootstrap procedure (Anguita et al., 2012). In this preliminary work authors decided to apply the Deep Extreme Learning Machines (DELM) algorithm (Oneto et al., 2017) to build the predictive model of the fuel consumption which is a state of the art tool which allows both to build an expressive representation of the data, the feature selection process, and the prediction model (Tang et al., 2015).
Once the DELM regression model is built and has been confirmed to be a sufficiently accurate representation of the real vessel fuel consumption, the authors applied the model in Phase II for fuel consumption prediction.
In particular, a set of new data $T_k = \{(x_1, y_1), \dots, (x_k, y_k)\}$, from t_1 to t_{end} has been used to create the model outputs $\{\hat{y}_1, \dots, \hat{y}_k\}$ given the inputs $\{x_1, \dots, x_k\}$. This prediction has been compared with the real fuel consumption values $\{y_1, \dots, y_k\}$ and the residual between the prediction and the actual consumption ϵ $\{\epsilon_1, \dots, \epsilon_k\}$ has been computed. These residuals error has been modelled as a time series, and a linear model has been applied to forecast the error trend since it was the simplest model suited given the knowledge of the fouling phenomena. The next step is the identification of the change in behaviour due to maintenance. To perform this detection, the

authors checked in time domain when the linear model was not suited anymore for describing the behaviour of the time series. By analysing the change in the distribution of the errors between the forecasted increase in fuel consumption and the actual time series of the residuals it was possible to detect this behavioural change by means of a Chi-Square Test.

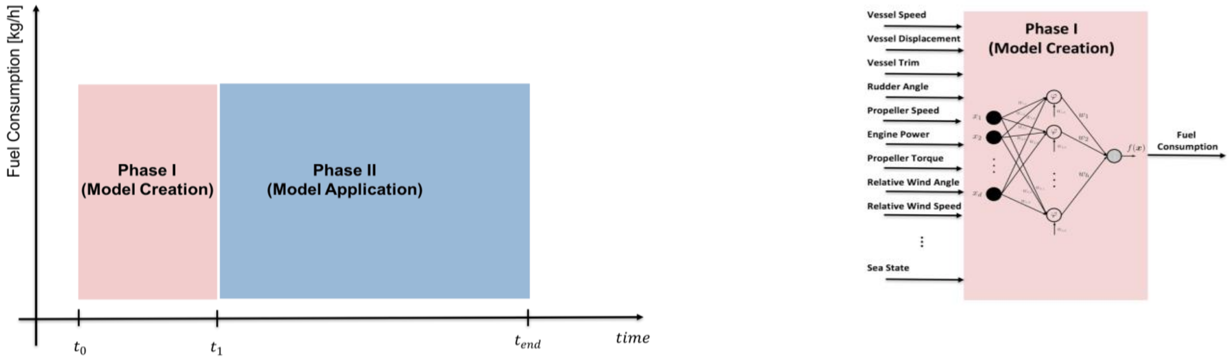


Figure 4: Two-step data analytics ML techniques proposed

The final result is reported in Figure 5, where the time series of the residuals are represented by the blue points, while the red lines represent the forecasted values of the time series based on the linear model. Finally, the green lines are the detected change in the behaviour.

4. RESULTS AND DISCUSSION

In this section, the authors report the results obtained by a two-step data analytics ML technique. The results of the application of the method above are proposed in Figure 5. Despite the inaccuracies of the sensors, the proposed ML analysis allows identifying a clear trend in the performance of the vessel. The slow, continuous decline in the vessel performance can be explained by the increase in hull and propeller fouling, while the discontinuities in the behaviour of the curve are related to relevant events in the ship's operational history as reported in Table 6.

Table 6: Vessel's maintenance events

Date	Event
November 2012	Propeller cleaning
March 2013	Hull cleaning
October 2013	Loss of the LOG speed measurement
September 2014	Change from fixed-speed to variable-speed operations

As can be noted from Figure 5, the model was able to capture these events while providing a good estimate of the loss of performance due to hull and propeller fouling. The loss rate (roughly 1% every two months) is consistent with the literature on the subject and with working experience.

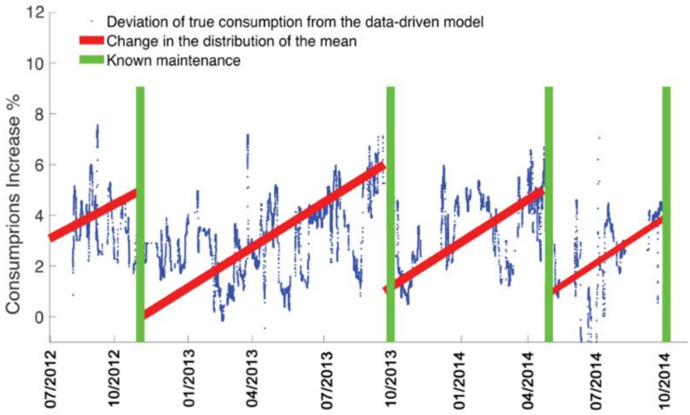


Figure 5: Two-step data analytics ML technique - results

5. CONCLUSIONS

In this paper, the authors presented the application of a two-step data analytics ML techniques for the prediction of ship performance. This method proved to be successful in the identification of relevant events in the ship's operational history (as a validation of its effectiveness) and showed its potential in evaluating the loss of performance of the ship over time due to hull and propeller fouling.
The application of this method can thus be considered to be of particular use in a number of relevant ships operational activities: from the determination of the right intervals between maintenance actions (propeller and hull cleaning) to the efficiency of these measures. Although this was not tested in this case study, the method can be foreseen to be of use also for the evaluation of energy-saving technologies, such as new propeller designs, sails. We see the contribution of this work as a necessary development for speeding up the uptake of new technologies, particularly for providing a better way to estimate performance and compare it to a reliable benchmark.

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