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MACHINE LEARNING METHODS IN MONITORING OPERATING BEHAVIOUR OF MARINE TWO-STROKE DIESEL ENGINE

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Abstract. The aim of this article is to enhance performance monitoring of a two-stroke electronically controlled ship propulsion engine on the operating envelope. This is achieved by setting up a machine learning model capable of monitoring influential operating parameters and predicting the fuel consumption. Model is tested with different machine learning algorithms, namely linear regression, multilayer perceptron, Support Vector Machines (SVM) and Random Forests (RF). Upon verification of modelling framework and analysing the results in order to improve the prediction accuracy, the best algorithm is selected based on standard evaluation metrics, i.e. Root Mean Square Error (RMSE) and Relative Absolute Error (RAE). Experimental results show that, by taking an adequate combination and processing of relevant sensory data, SVM exhibit the lowest RMSE 7.1032 and RAE 0.5313%. RF achieve the lowest RMSE 22.6137 and RAE 3.8545% in a setting when minimal number of input variables is considered, i.e. cylinder indicated pressures and propulsion engine revolutions. Further, article deals with the detection of anomalies of operating parameters, which enables the evaluation of the propulsion engine condition and the early identification of failures and deterioration. Such a time-dependent, self-adopting anomaly detection model can be used for comparison with the initial condition recorded during the test and sea run or after survey and docking. Finally, we propose a unified model structure, incorporating fuel consumption prediction and anomaly detection model with on-board decision-making process regarding navigation and maintenance.

Keywords: energy efficient shipping, propulsion engine, condition based maintenance, sensory data, machine learning, regression estimation, anomaly detection.

Notations

AIC – Akaike information criterion;
CBM – condition-based maintenance;
CFD – computational fluid dynamic;
CoCoS-EDS – computer controlled surveillance engine diagnostic system;
CRISP-DM – cross-industry standard process for data mining;
CV – cross validation;
DELM – deep extreme learning method;
DWT – deadweight tonnage;
ECS – engine control system;
ELM – extreme learning machine;
EVF – extreme value factor
FCM – fuzzy *c*-means
FOC – fuel oil consumption
GKNN – generalized *k*-nearest neighbour classification;
GLM – generalized linear model;
IMO – International Maritime Organization;
IoT – internet of things;
ISO – International Organization for Standardization;
IQR – interquartile range
LS – logarithmic transformation;
LS-SVM – least-squares support vector machines
MCR – maximum continuous rating;
MEP – mean effective pressure;
MEPC – Marine Environment Protection Committee;
MLP – multilayer perceptron;
NCR – normal continuous rating;
PMI – pressure mean indicator;
PSO – particle swarm optimization;
RAE – relative absolute error [%];
RBFNN – radial-basis function neural network;
RF – random forest;

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RMSE – root mean square error;
RPM – revolutions per minute
RVM – relevance vector machine;
SA – simulated annealing;
SMO – sequential minimal optimization;
SMOreg – sequential minimal optimization (regression);
SOM – self-organizing map;
SVM – support vector machine.

Introduction

With the development of technology, the volume of data generated by the ship's alarm and monitoring system is rapidly growing (Rødseth *et al.* 2016), even with its basic functionality of providing the ship's officers the principal alarm and status information to maintain safe and efficient operation of the machinery and related equipment. Data collected on-board, provide more information than human operator can comprehend; hence those data need to be fast and accurately processed and transformed into useful information and knowledge. Analytical tools enable the analysis of gathered sensory data in order to gain the insights that supports the decision-making process in ship operations (Murphy 2006; Kelleher *et al.* 2015).

IMO, through its MEPC recognize the most appropriate, efficient and feasible plans for energy savings and encourage goal setting and actions to reduce energy use on seagoing ships. Setting achievable goals creates an incentive and increases the commitment of participants in the process to improve energy efficiency. Regardless of the specifics of the goal, the process must be measurable and easy to understand (MEPC 2016). Fuel consumption non-linearly depends on ship navigating speed and propulsion engine load and technologies and procedures used in the maritime industry to, in some way, achieve energy goals mainly rely on that assumption (OCIMF 2011; Faber *et al.* 2011).

Preventive CBM is maintenance strategy that triggers maintenance activities when necessitated by the condition of the asset system. This approach enables, by continuous gathering of relevant data, determining the conditions of in-service assets to predict potential degradations and to plan, consequently, when maintenance activities will be needed and should be performed to minimize potential disruptions. CBM thus imposes the diagnosis of the potential problems and accurate, and timely identification of countermeasures and adjustment of time between maintenance by exploiting the collected data (Vorkapić *et al.* 2017). The purpose of monitoring the internal combustion engine indicator diagrams is to provide feedback on how the engine performs in the ship's life enabling optimum combustion and early detection of possible abnormalities that may cause the down performance.

Since the condition of the propulsion engine, hull and propeller deteriorate over time, it is necessary to distinguish the fraction of degradation of the propulsion engine from the degradation of hull and propeller, in which propulsion engine fuel consumption real-time monitoring and performance benchmarking can be of great benefit. The need for fast, reliable and adaptable analytical tool is increasing with novel legal requirements for energy consumption optimization and reduction of the carbon dioxide emissions from marine ships. Predictive model can help designers to gain insights into performance results already during design phase, avoiding long and expensive experimenting with the ship's engines. In order to build up the effective operational behaviour model of the diesel engine, it is critical to employ a suitable monitoring algorithm. This article aims at solving the problem of preventive monitoring by employing the machine learning model that integrates the propulsion engine fuel consumption prediction, operational parameters monitoring and outliers and extreme values detection aligned with existing ship-based decision-making processes, thus enabling support with navigation and maintenance. In short, we will show that proposed model efficiently supports decisions during ship's operations and maintenance.

The article is structured as follows: Introduction presents the problem; Section 1 provides review of the previous research and presents the research goals; Section 2 presents data source and data preparation, machine learning algorithms and evaluation metrics; Section 3 validates machine learning methods and illustrates the results obtained, followed by Conclusions section, which discusses the results and sets guidelines for future research plans.

1. Related works

In the previous research, engine modelling methods are broadly classified into two groups: white-box and black-box methods. The white-box identification technique derives the engine models by resorting to physical laws. Examples of white-box identification on a diesel engine include CFD models (Reitz, Rutland 1995; Payri *et al.* 2004), chemical kinetic models (Westbrook *et al.* 2006; Ra, Reitz 2008) and analytical multi-zone models (Benajes *et al.* 2016; Neshat *et al.* 2017). These mathematical models are difficult to exploit due to numerous physical parameters and complex assumptions, which are demanding for estimation, particularly for engine operators. Therefore, black-box methods are preferable nowadays because they model the systems in terms of its inputs and outputs (or transfer characteristics), without deep knowledge of its internal structure. Data mining, as an example of a black-box method, learns the relations between the input signals (variables) in the form of the trained model. In predictive modelling the main ability of the model is to provide accurate prediction for situations, which are not identical, yet similar to previously recorded and observed situations included in the training data (Gori 2017). Additional benefit of the utilization of data mining models in ship's operations modelling stems from its ability to solve demanding problems that require continuous adaptation to the real (current) situation of the ship. Several recent studies have investigated various data mining approaches to create an engine model for various purposes. Wong *et al.* (2013a, 2013b) create the model to determine the optimal biodiesel ratio that can achieve the goals of fewer emissions and improved fuel economy by using optimization methods SA and PSO based on advanced machine learning techniques, namely ELM, LS-SVM and RBFNN. For training, 60 instances of the engine data with installed dynamometer from four-cylinder, four-stroke direct-injection diesel engine Isuzu 4HF1, 88 kW/3200 RPM, 285 Nm/1800 RPM, naturally aspirated and water-cooled, are used. Experimental results show that, in terms of the model accuracy and training time, ELM with the LS is preferable over LS-SVM and RBFNN, regardless if it is with or without the LS. The results also indicate that PSO outperforms SA in terms of fitness and standard deviation, within acceptable computational time. The same authors present a model of diesel engine performance and emission characteristics performance using LS-SVM, RVM, basic ELM and kernel-based ELM on 24 instances of four-stroke diesel engine sensor data (dynamo measured torque, various engine sensor data and gas analyser data). The evaluation results show that kernel-based ELM with the LS and hybrid inference is better than other machine learning algorithms, in terms of prediction accuracy and training time (Wong *et al.* 2013a, 2013b). Machine learning is the core methodology used for prediction of the four-stroke engine torque by training the artificial neural network model from 60 instances of sensor data collected from the diesel engine and dynamometer (Cirak, Demirtas 2014). Namely, collected variables are engine speed, exhaust gas temperature, coolant temperature, torque and fuel mixing data (ratio between biofuel and euro-diesel fuel). The engine is four-stroke, four-cylinder, with a diameter of 79.5 mm with maximum power of 72 kW and maximum torque of 165 Nm. Authors report the high prediction results for engine torque with correlation coefficient of 0.99. Chan and Chin (2016) present the predictive model of marine engine performance by employing neural networks, multiple linear regression and bagged regression tree model. FCM clustering and SOM are reported as beneficial in reducing the RMSE of the predicted model. Operational data were collected from a containership with principal dimensions of $328 \times 46 \times 9.7$ m. The data is consisted of twenty- four inputs and five output variables with a total of 732 instances (reduced to 491 instances after removing the negative values), measured at an interval of four-hours for the period 1 July – 30 October 2014. The five output variables, i.e. shaft power, shaft RPM, shaft torque, engine power and turbocharger RPM were used as prediction output targets. Results indicated that neural network predictor performed better for shaft power, shaft revolutions and shaft torque with the necessity for a certain level of human intervention during analyses and data clustering. Coraddu *et al.* (2017, 2019) in their works address the problems of early detection of speed loss and hulls fouling employing OCVM, GKNN and ISO 19030-1:2016, ISO 19030-2:2016, ISO 19030-3:2016 methods and DELM using sensory, meteorological and oceanographic data of available vessels (research vessel *Princess Royal* and two *Handymax* chemical/product tankers). Results show the effectiveness of the proposal and its better prediction of the accuracy and reliability, with respect to the ISO 19030-1:2016, ISO 19030-2:2016, ISO 19030-3:2016.

It is apparent that aforementioned publications do not use cylinder pressure input necessary for an evaluation of the operational efficiency of the internal combustion engine. Furthermore, methodologies for the estimation of fuel consumption of diesel engines with data mining approach process utilize limited number of training and testing instances. None of the reported studies is related to the two-stroke engines of the new generation nor deals with machinery maintenance. Finally, listed publications do not provide single stop solution, i.e. from the initial data collection to on-board application and system integration. This detected gaps, are addressed in this study, where we present the model that integrates the propulsion engine fuel consumption prediction, operational parameters monitoring and outliers and extreme values detection aligned with existing ship-based decision-making processes. The goals are therefore set as follows:

- to create the model that may be used for accurate determining the propulsion engine fuel consumption and operational parameters monitoring in real environment;
- recognize the propulsion engine degradation throughout the exploratory time;
- propose structure that may be incorporated into the existing on-board decision-making process regarding navigation and maintenance.

2. Material and methods

Machine learning methods are data driven, so experimental data and data process analytics standardization is required for model training and verification. In this study, standard open process CRISP-DM 1.0 (Figure 1) is used (Chapman *et al.* 2000).

In this study, we address data mining goals in following steps (objectives):

- collection and understanding of sensory data from the prime move engine running in real environment;
- data preparation for machine learning;
- creation of data mining model employing linear regression (GLM), MLP, SVM[1] and RF capable of predicting the fuel consumption based on the input sensory data;
- selecting the best model based on the standard evaluation metrics with testing the model behaviour at a different number of input parameters (variables);
- establishing the method for engine parameters monitoring and evaluation.

Within the processing model, it is required to move back and for between the individual steps. The outcome of each step determines which phase, or phase task, shall be performed by the next. Arrows indicate the most important dependencies between the steps.

[1] *Weka* (*https://www.cs.waikato.ac.nz/ml/weka*) SVM implementation is using SMOreg algorithm (invented by John Platt) for solving the quadratic programming problems that arise during the training of support vector machines.

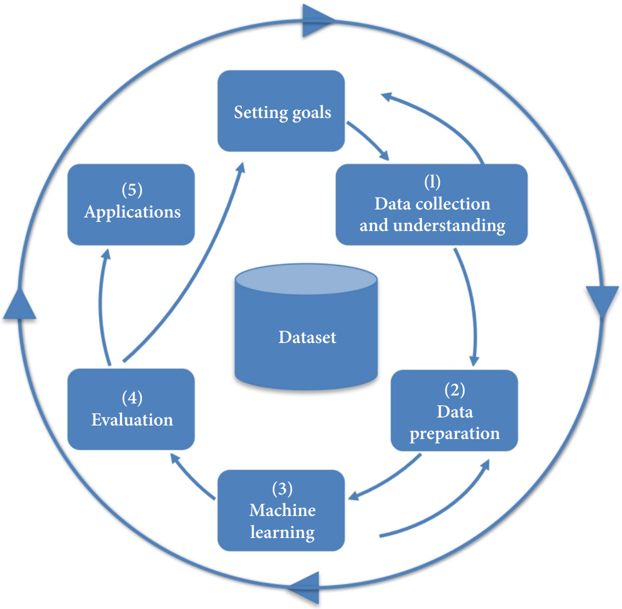

Figure 1. CRISP-DM 1.0 data mining process standardization

2.1. Data source and data preparation

In this study, propulsion engine sensory data from liquefied petroleum carrier similar to the recent series of the South Korean shipbuilder with a capacity of 54340 DWT, length 225 m, and width 37 m has been used for training and testing. The type and size of the ship was selected based on the fact, that its size was close to the average size of the ships commonly used on ocean-going voyages and that results may be applied on any similar ship. The main engine is a two-stroke marine diesel engine with one turbocharger unit. The maximum output power is 12400 kW, considering 15% sea margin and 10% engine margin for fouled ship hull and heavy weather, in order to satisfy the guaranteed speed of 16.8 knots at the design draft. Engine specifications are listed in Table 1.

Single four-blade fixed pitch propeller of 7400 m is directly connected to the main engine via shafting system. Propeller specifications are listed in Table 2.

Table 3 shows the input variables (collected sensory data): from 1 to 20 are the data from the main propulsion diesel engine MAN B&W 6G60ME-C9.2, PMI and CoCoS-EDS downloaded in a 7 s interval, while variables 21–31 have been collected from Kongsberg's *K-Chief 600* alarm, monitoring and control system at a 4 min interval (Kongsberg Gruppen 2020). The 7 s interval is the densest interval that can be retrieved by capturing the performance diagrams. The idea behind the 4 min interval dataset from the monitoring system is to provide the enrichment to the data collected in 7 s interval.

Shaft power (Item 2) is measured by the MetaPower's torque meter, while temperature (Items 21–30) and revolutions sensors (Item 1) are engine-maker originally fitted sensors integrated into *K-Chief 600* alarm and monitoring system architecture (Kongsberg Gruppen 2020. In order to analyse the combustion process and measure the pressure in the cylinder (Items 3–20) ECS is using Kistler's *6613EQ13-C* online combustion control piezoelectric sensors mounted directly at each cylinder indicator cock. The online sensors were calibrated prior to collecting the data according to requirements stated in the IMO NO_x regulations and according to the manufacturer's recommendation (IMO 2011). Calibration is done using a dedicated, certified reference sensor, thus making it traceable to standards recognized by the classification society. The reference sensor is a hand-held sensor attached to the PMI calibration box. Measurement event log did not indicate a difference between measurements made online and reference sensors. Fuel oil mass flow (Item 31) is measured by *Endress + Hauser's Proline Promass 80*, *Coriolis Mass Flow Measuring System* made as per ISO 11631:1998 with total error of 0.15%. Two flow meters of the same type have been installed, one at the engine fuel inlet, the other at the fuel outlet line, and the difference between the readings presents the consumed fuel oil.

The readings of sensory data were conducted at engine speeds of 89 min^{-1} (NCR), 85 min^{-1} (requested speed setting during sailing) and 75 min^{-1} (economic speed above auxiliary blowers cut in pressure), with different engine loads ranging between 5712…10164 kW measured at the shaft, resulting in 1018 instances of sample data at a time interval of 7…8 s. To ensure the repeatability and comparability of the measurements, the engine outlet cooling water temperature was automatically controlled by a temperature controller to 89 °C, while the engine outlet lubricating oil temperature was automatically controlled by a temperature controller between 45…47 °C. Additional details about sampling are in the Table 4.

Table 1. Specifications of the marine diesel engine

Engine model		MAN B&W 6G60ME-C9.2
Engine type		Electronically controlled, two-stroke, direct reversible, crosshead-type diesel engine with constant pressure turbo charging, compliant with IMO Tier II requirements
Bore		600 mm
Stroke		2790 mm
Number of cylinders		6
MCR	output	12400 kW
	revolution	92.2 min^{-1}
	MEP	17.0 kg/cm^2
	peak maximum cylinder pressure (p_{max})	185 kg/cm^2
	mean piston speed	8.6 m/s
	fuel consumption (42700 kJ/kg)	161.3 g/kWh
NCR	output	11160 kW
	revolution	89 min^{-1}
	MEP	15.9 kg/cm^2
Turbocharger model and type		Hyundai-ABB A175×1 set

Table 2. Specifications of the propeller

Propeller model and type	HHI Keyless, FPP
Diameter	7400 mm
Number of blades	4
Mean pitch	5971.06 mm

Table 3. Input variables list (sensor data)

No	Description	Unit
1	RPM	min^{-1}
2	Shaft power	kW
3	p_{comp} (compression pressure), cylinder 1	bar
4	p_{comp}, cylinder 2	bar
5	p_{comp}, cylinder 3	bar
6	p_{comp}, cylinder 4	bar
7	p_{comp}, cylinder 5	bar
8	p_{comp}, cylinder 6	bar
9	$p_{\max}$ (peak maximum cylinder pressure), cylinder 1	bar
10	$p_{\max}$, cylinder 2	bar
11	$p_{\max}$, cylinder 3	bar
12	$p_{\max}$, cylinder 4	bar
13	$p_{\max}$, cylinder 5	bar
14	$p_{\max}$, cylinder 6	bar
15	p_i (indicated pressure), cylinder 1	bar
16	p_i, cylinder 2	bar
17	p_i, cylinder 3	bar
18	p_i, cylinder 4	bar
19	p_i, cylinder 5	bar
20	p_i, cylinder 6	bar
21	MS114 ER ambient air temperature	°C
22	MA007 ME exhaust gas temperature, cylinder 1	°C
23	MA008 ME exhaust gas temperature, cylinder 2	°C
24	MA009 ME exhaust gas temperature, cylinder 3	°C
25	MA010 ME exhaust gas temperature, cylinder 4	°C
26	MA011 ME exhaust gas temperature, cylinder 5	°C
27	MA012 ME exhaust gas temperature, cylinder 6	°C
28	MA013 ME TC out temperature	°C
29	MA014 ME TC in temperature	°C
30	AB018 EGE exhaust gas outlet temperature	°C
31	ME_tot_FL	kg

Table 4. Sampling series with time stamp intervals

Sampling series No	RPM setting $[min^{-1}]$	Number of instances	%	Time interval
1a	85	400	39.29	May 2016
1b	85	4	0.39	November 2016
1c	85	10	0.98	December 2016
2a	89	199	19.55	January 2017
2b	89	10	0.98	January 2017
2c	89	162	15.92	February 2017
3	75	233	22.89	February 2017
Summary	–	1018	100	–

In the first series of retrieving the sensor data, the engine was tested with high sulphur heavy fuel oil, compliant to ISO 8217:2017 standard, whose main properties are as follows: density @15 °C (ISO 12185:1996) 985.5 kg/m^3, viscosity @50°C (ASTM D7042-20) 346.2 mm^2/s, sulphur (ISO 8754:2003) 2.42% m/m, and net specific energy (ISO 8217:2017) 40.33 MJ/kg, while in the series 2–3, the fuel had density @15°C (ISO 12185:1996) 985.3 kg/m^3, viscosity @50°C (ASTM D7042-20) 345.2 mm^2/s, sulphur (ISO 8754:2003) 2.41% m/m, and net specific energy (ISO 8217:2017) 40.33 MJ/kg. Since both fuels have similar characteristics, no correction was found necessary.

In order to minimize errors, eliminate noise, faulty or non-existing signals, the data set has to be filtered before further analysing (Rødseth *et al.* 2016; Mirović *et al.* 2018). However, employment of various solutions may also cause loss of valuable information (Vlahogianni 2015). In some cases, additional and possibly unavailable information is needed for correct interpretation. Finally, our approach is to use raw data and rely on measures that are already built in the existing systems; in the event of sensor failure, the same is triggering the alarm. In the future similar interconnection will be included in the signal pre-processing architecture thus marking such signals as invalid.

2.2. Machine learning algorithms

For the training of models, a software toolkit *Weka* (version 3.8.2)[2] is used employing following algorithms with highlights on the distinguishing features from standard implementations (Witten *et al.* 2017).

GLM (o linear regression) is a numerical prediction algorithm that works by estimating the coefficients for the line or hyper-plane that best fits the learning data. It is a simple regression algorithm, fast to build, and achieving good prediction results, especially when the output variable is a linear combination of input variables. If the data shows lack of a linear dependence, then the process will find the best straight line (linear direction) so that the RMSE is interpreted as the best result. Linear models, despite modelling simple linearity, serve as blocks or starting points for more complex learning methods. In Weka, the linear regression algorithm uses the AIC for selecting the best model. The AIC is an estimator of the relative quality of statistical models for a given dataset. Given the set of models for the data, the AIC evaluates the quality of each model relative to every other model. Accordingly, AIC provides the means to select a model, and it is calculated by the expression:

$$AIC_{result} = -LL + N, \tag{1}$$

where: AIC_{result} – resulting Akaike information criterion; N is the number of parameters; LL is the logarithm of the

[2] *Weka* is an open access software toolkit developed at the University of Waikato (New Zealand) and written in the *Java* programming language. It is designed to solve data mining tasks using integrated tools for preparation, classification, regression, grouping, association mining, and data visualization.

probability with a negative sign to minimize the result (Witten *et al.* 2017).

MLP is a supervised feedforward neural network that simulates the structure of the human brain using a network of artificial neurons with at least three layers of neurons (Buhmann 2003). Each neuron, except the one in the first layer, has a non-linear activation function. The first layer is an input layer, and it contains as many neurons as there are features (input variables) in the training data. The layers are fully connected, which means that each neuron in one layer is connected to each neuron in the next layer. During the regression in a neural network, the input signals travel through neural connections, multiplying with weights before entering the next neuron, where all the values are summed up and added to bias. The calculated value is then passed to the activation function. For the training of neural network, a backpropagation algorithm is used, which, taking into account the loss function gradient, adjusts weights factors in order to obtain better predictions. A common function for the hidden layers is the sigmoid function (Haykin 2009; Shalev-Shwartz, Ben-David 2014).

SVM implements for regression. Considering a data set $\{(x_1, y_1), ..., (x_n, y_n)\}$ with $x \in R_d$ (d-dimensional input space) and $y \in R$, support vector tries to find the function $f(x)$, which relates the measured input object to the desired output property of an object (Gunn 1998; Shalev-Shwartz, Ben-David 2014). The parameters are learned using modifications to the Smola and Schölkopf's SMO algorithm (Smola, Schölkopf 2004), which demand that the kernel matrix is computed and stored in memory. This requires large memory and involve expensive matrix operations such as Cholesky decomposition of a large submatrix of the kernel matrix (Dereniowski, Kubale 2004). Third, coding of these algorithms is difficult. Therefore, used modifications to the SMO introduced by Shevade *et al.* (2000) significantly speed up the SMO algorithm in most of the situations.

The Pearson VII universal kernel (*Puk*) function was developed by Karl Pearson in 1895 and it is used as a vector support function. The basic form of the Pearson VII function for curve fitting purposes is in the equation (Üstün *et al.* 2006):

$$f(x) = \frac{H}{\left(1 + \left(\frac{2 \cdot (x - x_0) \cdot \sqrt{2^{\frac{1}{\omega}} - 1}}{\sigma}\right)^2\right)^{\omega}}, \quad (2)$$

where: H is the peak height at the center x_0 of the peak; x represents the independent variable. The parameters σ and ω control the half-width (also named Pearson width) and the tailing factor of the peak. The main reason to use the Pearson VII function for curve fitting is its flexibility to change, by varying the parameter ω, from a Gaussian shape (ω approximates infinity). Compared to the commonly applied kernel functions, the use of the *Puk* has two main advantages: on the one hand, it does not require making a selection out of the kernel functions, which simplifies the model building process and saves computing time, and on the other hand, it has a stronger mapping power, through which it can properly deal with a large variety of mapping problems.

RF is an algorithm used for constructing a forest of random trees by using bagging sampling techniques (Breiman 1994; Dietterich 2000). The trees in RF are constructed in parallel and there is no interaction between the trees during building process. RF employed for regression learning operates by constructing a set of decision trees at training time and outputting the class that is the mode of mean prediction of the individual trees. A RF combines the results of multiple predictions, which aggregates prediction of individual decision trees and with modification that prevents trees from being highly correlated. The RF algorithm ensures that the ensemble model does not rely too heavily on any individual feature, and makes fair use of all potentially predictive features. Each tree draws a random sample from the original set of instances when generating its splits, adding a further element of randomness that prevents overfitting.

2.3. Evaluation metrics

Standardly the data set is split into two independent sets: training and testing set. k-fold CV technique partitions the training dataset into k subsets and rotates them k times for the validation thus expanding the initial quantity of data k times. Usually $k = 10$ (Figure 2) and each of 10 subsets is systematically applied for training and validation of the models. The set used for training is not used for validating nor the validating set is used for algorithm training. Final accuracy is an average of each round validation result. k-fold CV is preferred method with smaller datasets as data is expanded by the number of rotations (Kelleher *et al.* 2015; Witten *et al.* 2017).

In order to test the performance of the trained models in every possible scenario, we employed a 10-fold CV method within Weka toolkit on 80% of instances on computer with 1.4 GHz processor and 4 GB 1600 MHz DDR3 memory. Upon selection of the best algorithm, results are confirmed on remaining 20% of instances reserved for testing.

Next, we use following evaluation measures implemented in *Weka* as well:

– RMSE is commonly used measure calculated using the expression:

$$RMSE = \sqrt{\frac{(y_1 - a_1)^2 + \ldots + (y_n - a_n)^2}{n}}; \quad (3)$$

– RAE is using relative values and calculated according to the following expression:

$$RAE = \frac{|y_1 - a_1| + \ldots + |y_n - a_n|}{|\bar{a} - a_1| + \ldots + |\bar{a} - a_n|} \cdot 100\%. \quad (4)$$

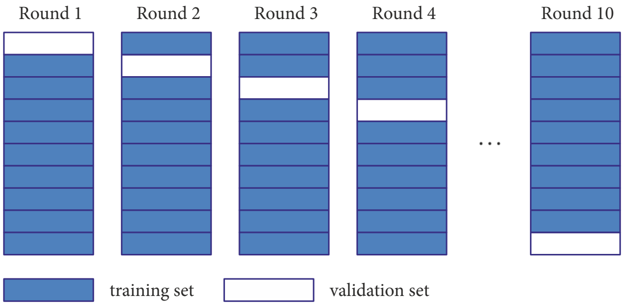

Figure 2. 10-fold CV

The correlation coefficient C_c measures the statistical correlation between the predicted values of $y_1, y_2, ..., y_n$ and the true values of $a_1, a_2, ..., a_n$. The correlation coefficient ranges from 1, for perfectly correlated results, to 0, when there is no correlation, and −1, when the results are perfectly negatively correlated. The correlation captures slightly different information then other evaluation measures because it depends on the scale in the following sense: if a given set of predictions is taken, the error remains unchanged if all the predictions are multiplied by a constant factor and the true values remain unchanged. This factor appears in every S_{ya} expression in the numerator and in every S_y and S_a expressions in the denominator, thus invalidating it. The correlation coefficient is calculated according to the following expression:

$$C_c = \frac{S_{ya}}{\sqrt{S_y \cdot S_a}}, \quad (5)$$

where is:

$$S_{ya} = \frac{\sum (y_i - \bar{y}) \cdot (a_i - \bar{a})}{n-1}; \quad (6)$$

$$S_y = \frac{\sum (y_i - \bar{y})}{n-1}; \quad (7)$$

$$S_a = \frac{\sum (a_i - \bar{a})}{n-1}, \quad (8)$$

where: $\bar{y}$ represents the mean over the predicted values; $\bar{a}$ represents the mean over the true values.

The results visualization provides an overview of regression modelling by selecting the true values of $a_1, a_2, ..., a_n$ on the x axis, and predicted values of $y_1, y_2, ..., y_n$ on the y axis. Outliers and extreme values (anomaly detection) recognition in *Weka* is based on the interquartile range (Witten *et al.* 2017):

$$Q_3 + OF \cdot IQR < x \le Q_3 + EVF \cdot IQR,$$

or

$$Q_1 - EVF \cdot IQR \le x < Q_1 - OF \cdot IQR \quad (9)$$

and extreme values are in:

$$x > Q_3 + EVF \cdot IQR,$$

or

$$x < Q_1 - EVF \cdot IQR, \quad (10)$$

where: Q_1 is 25% quartile; Q_3 is 75% quartile; OF is outlier factor;

$$IQR = Q_3 - Q_1. \quad (11)$$

3. Results and discussion

In this study, the propulsion engine fuel consumption was selected as the output variable on recorded 1018 instances per three RPM settings (Table 4) and in different setups and weather conditions, enabling better captioning of standard seagoing scenarios. Measurements with fewer instances, i.e. 1b, 1c and 2b represent conditions of the calm sea that are significantly different from those of the basic measurements in rough sea conditions and a large number of instances at the same propulsion engine revolutions. The exception is data set 3 for the set RPM without rough sea recordings.

GLM achieved the result of RMSE 12.9081, RAE 3.6001% and C_c 0.9991.

MLP with initial setup with one hidden layer with 5 nodes, momentum 0.2, learning rate 0.3 and 500 epochs achieves RMSE 13.6072, RAE 3.6068% and C_c 0.9991. Increasing the number of hidden layers to 2 improves the model because adding layers enables modelling of nonlinear complexity: the setup with 2 hidden layers and 10 nodes achieves the best result with RMSE 12.475, RAE 3.3824% and C_c 0.9992.

SVM by using the polynomial kernel performs with RMSE 1.3873, RAE 0.3663% and C_c 0.9989. Since the best result can only be achieved if suitable kernel function is applied, the *Puk* function was chosen. Changing support vector to *Puk*, predication improved to RMSE 7.1032, RAE 0.5313% and C_c 0.9997.

RF trained the model in 0.1 s with the RMSE 10.1746, RAE 2.1769% and C_c 0.9994. By reducing the number of input variables to the number of revolutions of the propulsion engine (RPM) and the indicated cylinder pressures p_i, the RF algorithm achieves RMSE 22.6137, RAE 3.8545% and C_c 0.9973. Reducing the number of variables according to the variable importance is a well-known characteristic of RF algorithm used for the construction of smaller and yet not inferior model, which is more appropriate for the use in praxis (Breiman 2001; Breiman, Cutler 2004).

Visual presentation of results shown on Figure 3 verifies SVM's the smallest dispersion of fuel consumption prediction results over measured consumption.

The final decision on a suitable algorithm depends on the end use, namely fewer variables required for quality prediction (such as RF) can be prevalent, especially for models that work with many instances and large data amount and require longer processing time and more demanding platforms. Conversely, if high prediction accuracy is a priority, then the choice falls on the SVM driven model.

Furthermore, it is possible to set up a model on the same dataset by applying an unsupervised filter (*weka.filters.unsupervised.attribute.InterquartileRange*), based on the IQR, for detecting outliers and extreme values (anomaly detection). This model may evaluate the running conditions and recognize unusual states (marked in red colour) of the engine or early engine performance degradations as presented in Figure 4. The value of the deviation (factor) can be adjusted to accommodate the actual needs and recommendations of the manufacturer, namely the minor deviation may be within tolerable limits, and therefore the value of such information is small. In the presented case, since it is a newly build ship with clean hull and propeller, according to the diagrams there is no indication of engine degradation, but on the contrary increase of cylinder pressures and $p_{\max}/p_{comp}$ ratio over maker's maximum recommended 35 kg/cm^2 is a consequence of the short-term over-response of the ESC while sailing in the bad sea conditions in tropical areas. Such deviations could easily be mitigated by changing the engine control from speed (engine revolutions) to rough sea mode, i.e. by distributing the load evenly across the cylinders and slowing down the governing response.

Standardly, elevated fuel consumption to deliver equal power to the shaft indicates an incorrect adjustment of the control system (engine out of tune), fuel injection equipment failure or excessive wear of the moving parts or issue with quality and calorific value of the fuel. The detected change in pressures inside the cylinder can assist the operator in the further diagnosis of failures and early warning of irregularities. By monitoring the combustion pressures, it is possible to recognize the booster pumps or fuel injectors failures, while compression pressures monitoring makes it possible to assess the condition of the piston rings or perceive leaking exhaust valves. In each case, visual anomaly monitoring can assist the operator in detecting early faults and in deciding regarding upcoming maintenance.

The proposed model integration for installation onboard (presented in Figure 5) shows data handling framework with key elements (components) that share common attributes at the same resolution level and implemented on the respective layers of the data flow.

Model is directly integrated with existing ship's sensors and data acquisition system (A_1) and using the existing operating condition (A_3) and ship maintenance system (A_4) with added component, i.e. data storage and processing unit (A_2). Data storage and processing unit is consisted of pre-processing layer and parameter reduction, data driven models (i.e. digital models), storage drives. Although this study deals solely with main propulsion engine, vessel operating condition (and navigation condition) is included in this structure to obtain a meaningful data flow.

Ship's sensors and data acquisition system (A_1) is feeding the Data storage and processing unit (A_2) with (c_1) data $x_1(i_1)$, $x_2(i_1)$, …, $x_n(i_1)$; $x_1(i_2)$, $x_2(i_2)$, …, $x_n(i_2)$; $x_1(i_n)$, $x_2(i_n)$, …, $x_n(i_n)$, where n represents number of variables and i number of instances (time). A dynamic interaction between system components starts from data storage and processing unit (A_2) wherefrom output (predicted) variables and detected outliers (c_2 and c_3) assist in the decision-making process on the navigation identifying optimal vessel operating conditions to reduce the fuel consumption (A_3) and main propulsion engine maintenance (A_4) increasing the overall reliability. The feedback is embedded across the signals measured by associated sensors and collected at data acquisition unit (A_1). In shipboard environment, it is suggested that data is processed on-board to avoid the interruptions in data transmission and ensure continuous processing of a large number of sensory data, thereby providing operator support in real time. The im-

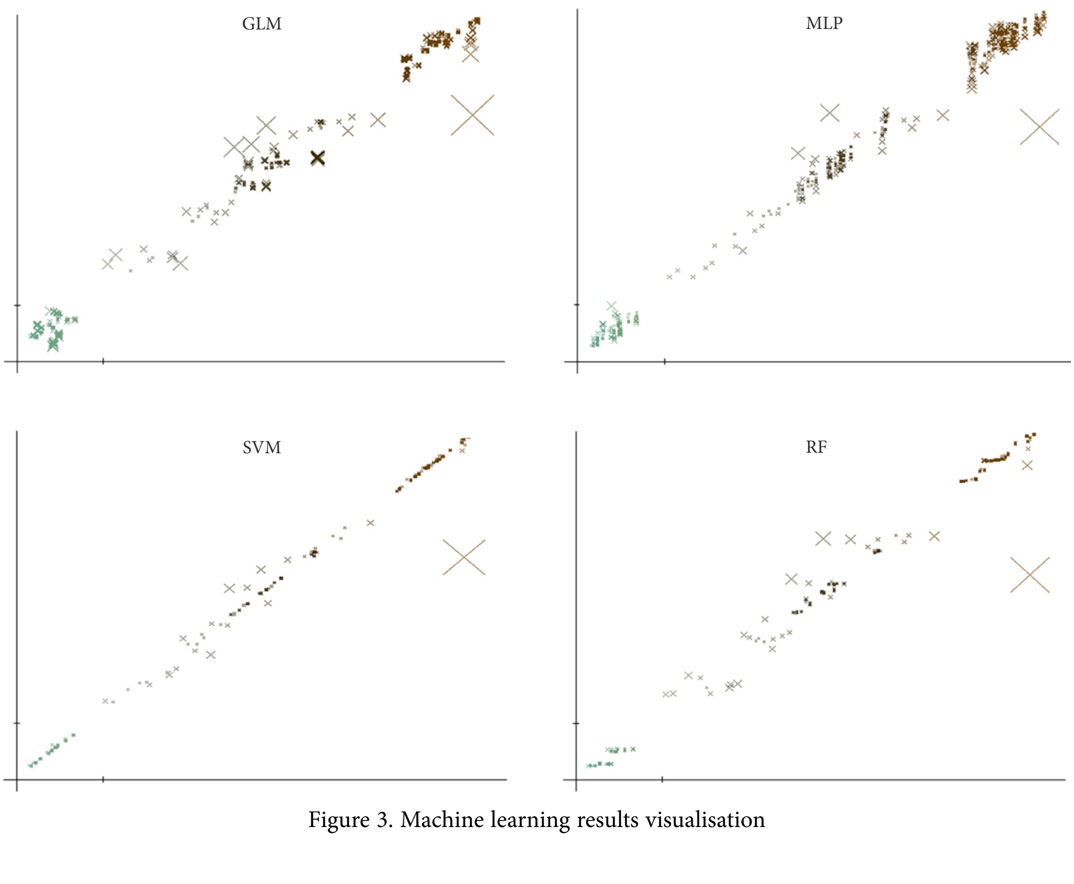

Figure 3. Machine learning results visualisation

proved propulsion engine performance and maintenance is varying in real time and it is most appropriate to be made as visualization layer displaying relative correlation value, i.e. s expected value vs. measured value for output variables, part of data storage and processing unit and supporting decision-making process data regarding navigation and system reliability (maintenance).

Authors contribution in the proposed methodology is in the inclusion of sensory data processed by machine learning and anomaly detection mining into existing on-board decision-making process regarding navigation and maintenance. The introduction of new information enables the acquisition of new knowledge on fuel savings as well as better management of ship processes. By introducing distinctive deviations from the normal operating mode, it is possible to improve the existing ship's maintenance system and early detection of malfunctions and deteriorations.

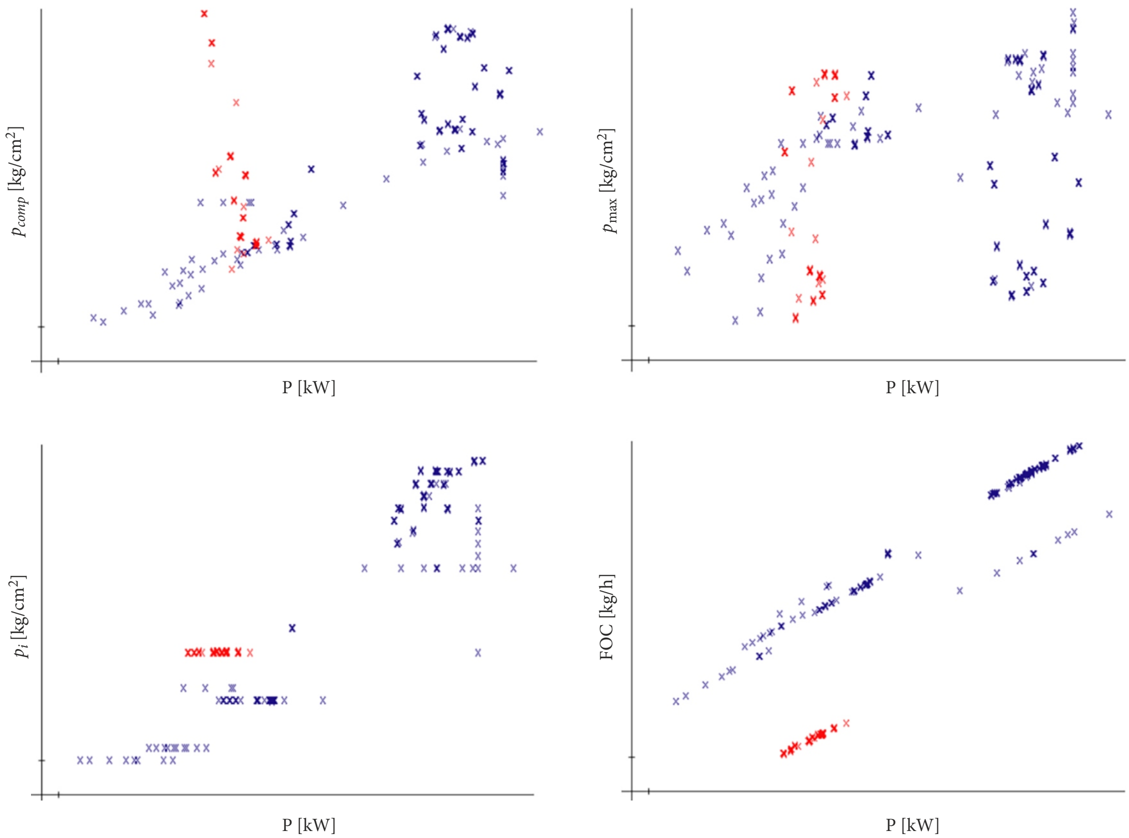

Figure 4. Operational parameters anomaly detection

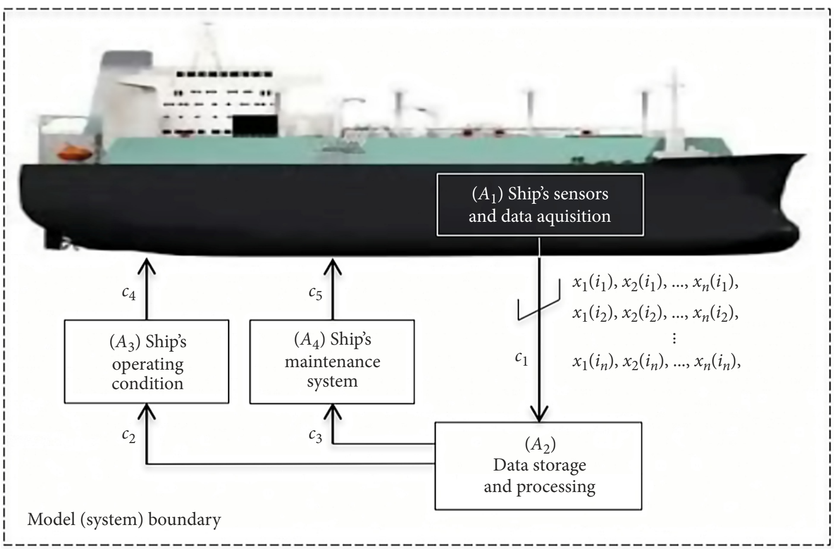

Figure 5. Model structure

Conclusions

In this study, models based on linear regression, MLP, SVM and RF have been applied to the problem of predicting fuel consumption of a two-stroke electronically controlled propulsion engine on the operating envelope. The models were trained from 31 sensory data taken from the existing alarm and monitoring system and the main propulsion ECS. An unsupervised anomaly detection filter was then applied to the same dataset with the aim of early detection of propulsion engine performance downgrade or failures. Finally, the article proposes an improved structure of the existing decision-making process with incorporated fuel consumption prediction and anomaly detection model.

This study has shown that by selecting an adequate combination and processing the relevant sensory data, it is possible to create a model that predicts fuel consumption of a diesel engine with RMSE 7.1032 and RAE 0.5313%, achieved by SVM, and similar by RF, MLP and linear regression. Evaluation results show that the RF achieve the best RMSE 22.6137 and RAE 3.8545% with the least input variables (cylinder indicated pressures and propulsion engine revolutions), i.e. slightly over performing SVM algorithms. These results confirm that data mining-based methods can be successfully used in a real time operational condition of the ship. By employing an unsupervised anomaly detection filter, it is possible to set up a method of evaluating propulsion engine relevant running parameters by comparing with the initial condition recorded during the test and sea run or after docking.

With the promising results obtained in this study, developed models transformed into exploratory or predictive analytical tool and integrated into the existing ship system, with minimum of intervention, may be used in establishing performance indicator for fuel consumption reduction according to ship's energy efficiency management plan. Results may be used in determining the fuel consumption margins in the charterer's parties and complementing the existing CBM methods or utilized in pinpointing the contribution of prime move engine degradation in the overall degradation of the vessel. The application of the proposed model adapted to carbon dioxide emission footprint can be beneficial in monitoring and estimating the emissions. The results can be used by the ship owner and operator to establish a system of monitoring and fuel consumption forecasting related to the binding requirements of the *MARPOL 73/78 Annex VI Regulation 22A* (IMO 2018) and the processes that are used to report the data to the ship's administration.

It is worth noticing that all data processing and exchange is executed on-board while the IoT will be an option in the near future, when broadband real-time data exchange is confirmed in practice. Given that, it is using data from main propulsion engine this study has limitations, which we plan to address in the future. We plan a thorough input data collection of the whole ship targeting the practical needs for comparison, including the addition of exogenous factors and training of additional models such as expanding the collected data to new navigational scenarios and testing of data mining algorithms. In such an extended model, the proposed model will serve to clearly segregate the impact of the propulsion engine from the ship as a whole.

Author contributions

Author contributions are:
- Aleksandar Vorkapić and Sanda Martinčić-Ipšić conceived the study and were responsible for the design and development of the data analysis;
- Aleksandar Vorkapić and Karlo Babić were responsible for data collection and analysis;
- Aleksandar Vorkapić, Radoslav Radonja, Sanda Martinčić-Ipšić were responsible for data interpretation;
- Aleksandar Vorkapić, Karlo Babić, Radoslav Radonja and Sanda Martinčić-Ipšić contributed equally in writing the article.

Disclosure statement

Authors declare no competing financial, professional, or personal interests from other parties.

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