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SHIP MACHINERY CONDITION MONITORING USING PERFORMANCE DATA THROUGH SUPERVISED LEARNING

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SUMMARY

This paper aims to present a methodology for intelligent monitoring of marine machinery using performance data. Monitoring of machinery condition is a crucial aspect of maintenance optimisation that is required for the vessel operation to remain sustainable and profitable. The proposed methodology will train models pertinent to specific machinery components using pre-classified performance data and then classify new data points using the models developed. For this, measurements are suitably analysed and processed to retain most of the information (variance) of the original dataset while minimising number of required dimensions. Finally, new data are compared against the models developed to evaluate their condition. The above will provide a flexible but robust framework for the early detection of emerging machinery faults. This will lead to minimisation of ship downtime and increase of the ship's operability and income through operational enhancement. Case studies that show initial results obtained through main engine data are included.

NOMENCLATURE

INCASS	Inspection Capabilities for Enhanced Ship Safety (EU FP7 Project)
C.F.W.	Cooling Fresh Water
C.W.	Cooling Water
L.O.	Lube Oil
MCR	Maximum Continuous Rating
M/E	Main Engine
NAOME	Naval Architecture, Ocean and Marine Engineering
NN	Neural Network
OEM	Original Equipment Manufacturer
PCA	Principal Component Analysis
SCADA	Supervisory Control and Data Acquisition
SRM	Structural Risk Minimisation
SVM	Support Vector Machine

1. INTRODUCTION

Ships are a significant asset of the global goods transportation system as over four-fifths of merchandise are carried by sea [1]. Current financial situation of the shipping industry combined with an average global merchant fleet vessel age of almost twenty years [1] make clear that a high level of operations optimisation is required for the vessel to remain sustainable and profitable.

Maintenance of a ship's machinery components can substantially affect the ship's sustainability and profitability. Meanwhile, current maintenance state-of-practice in shipping offers ample room for improvement. As such, the introduction of novel methods of monitoring the condition of machinery equipment, suggesting suitable maintenance actions, and scheduling those actions in an optimised fashion is significant.

Three main maintenance types exist: reactive, preventive, and predictive. Reactive maintenance concerns maintenance that is only performed once a component fails completely. Preventive maintenance refers to maintenance that happens at a fixed frequency, usually following Original Equipment Manufacturers (OEMs) recommendations. Preventive maintenance offers many benefits compared to reactive. However, preventive maintenance also exhibits multiple shortcomings such as high maintenance costs and significant (planned) downtime. An optimised maintenance scheme would offer extended machine lifespan, coupled with reduced maintenance costs and downtime. Such schemes are usually classified under predictive maintenance. Nevertheless, prerequisite for the development of any predictive maintenance system is a condition monitoring framework that can accurately estimate the condition of monitored systems, subsystems and components. This framework takes as input several measurements and analyses them appropriately to return an estimation of their condition as output. Two customary sets of measurements for condition monitoring are performance and vibration measurements. Performance measurements are a valid basis for the estimation of reciprocating machinery while offering the additional benefit of automatic acquisition in most applications. In the case of rotating machinery, vibration measurements can offer good insights but usually need to be manually acquired using specialised equipment.

While predictive maintenance is widely used in other fields such as nuclear power production and aerospace, there are not many applications in the marine field. Currently, most maintenance actions carried on board vessels can be classified as preventive maintenance. Hence, this paper aims to present the development of a framework concerning the processing of performance data and training of appropriate models for the condition monitoring of marine machinery.

Section 1 introduces the paper's scope and motivation of research. Section 2 refers to the research background. Section 3 elaborates on the proposed methodology concerning dimensionality reduction, data processing, and model training. Section 4 details the setup of multiple case studies used to validate the proposed methodology focusing on different main engine (M/E) components. Section 5 presents and discusses the results obtained through these case studies. Finally, in section 6, overall conclusions are provided along with further research steps.

2. RESEARCH BACKGROUND

In general, three types of maintenance are applicable for machinery applications: reactive, preventive, and predictive or condition-based.

Reactive (also known as run-to-failure, breakdown or corrective) maintenance concerns maintenance that is only performed following the complete failure of a component. At that point, no repairing is possible and the component is replaced by a new one [2]. In some cases, repairing is possible, albeit with a significantly increased cost as a large spare-parts inventory is required [3, 4]. This method of maintenance offers provides the longest time between shutdowns but failures are catastrophic and can possibly affect multiple components and/or machines [4]. Hence, reactive maintenance is mainly applied to relatively not expensive and non-critical machines or where redundancies have been implemented so that production is not interrupted.

Preventive maintenance refers to maintenance that happens at a fixed frequency, usually following Original Equipment Manufacturers (OEMs) recommendations. Compared to reactive maintenance, preventive maintenance offers significant increase in machine lifespan. This is because the probability of catastrophic failures is diminished. Additionally, preventive maintenance is more cost-effective as the number of components or machine that need complete replacement is reduced. Moreover, as a considerable tranche of maintenance is performed as a precaution and before the perception of any defects, unplanned downtime is reduced. Preventive maintenance generally aims to provide such maintenance intervals that only 1-2% of machinery experience failures between maintenance intervals [4]. Thus, the clear majority of machines would be able to continue working without maintenance for multiple maintenance intervals. This introduces increased “infant mortality” in machines, due to faults that would otherwise have been avoided [4]. Infant mortality concerns both failures caused by faulty replacements and by general tampering during maintenance activities. Besides, excessive maintenance causes significant, albeit planned, down- time. On top of that, unexpected failures still occur as maintenance happens at a fixed frequency, without taking into consideration the actual machine condition.

Predictive maintenance provides a more intelligent method of maintenance planning. There, present and past condition of each component is taken into consideration to offer bespoke maintenance scheduling for each component and each machine. Predictive maintenance requires a higher expenditure at installation but over an extended period, becomes more economical than preventive or reactive maintenance. Especially in industries where machines are expected to run for long periods without any shutdowns, it has been shown that predictive maintenance can reduce relevant costs by up to 65% [5]. Furthermore, in terms of downtime, planned downtime is minimised to the bare necessary minimum and unplanned is almost diminished. This optimised maintenance scheduling permits the maximisation of machine lifespan. Still, while predictive maintenance proves to be more economical during a machine’s lifespan, results take years to show.

2.1 MAINTENANCE IN THE MARITIME SECTOR

In sectors such as defence, aviation, manufacturing, automobile, and nuclear power production, maintenance focus has recently shifted from reactive to preventive/predictive. Ship maintenance amounts to 10-15% of the shipping company direct operating costs [7]. However, in the maritime sector, ship maintenance has been considered an area of needless expenditure and advanced monitoring methods have not yet been widely applied [8]. Nevertheless, some attempts towards predictive maintenance in shipping have been made in the past few years. For example, a methodology where vibration data are combined with performance data (cylinder pressures) for the condition monitoring of a main engine has been suggested [9]. Accordingly, a thermodynamic model of a main engine has been developed to perform condition monitoring using cylinder pressure traces [10]. Besides, a self-learning algorithm for fault diagnosis in the combustion system of a marine diesel engine has been developed [11]. Furthermore, a self-learning model for the condition monitoring of ship machinery based on vibration measurements was developed in [20].

2.2 PERFORMANCE MONITORING OF MACHINERY

Performance monitoring of machinery is a problem that requires the development of a suitable model. This model can either use a first-principles analysis (i.e. white-box model), or use a more ‘brute-force’ approach by developing a model using self-learning algorithms coupled with an acquired dataset (i.e. black-box model). Often, a combination of both techniques is applied, leading to grey-box models. [12] developed a framework for the analysis of data acquired through wind turbine SCADA (Supervisory Control and Data Acquisition) bus measurements to perform condition monitoring based on correlations between measurements. [13] and [14] both presented an overview of Support Vector Machine

(SVM) techniques for fault diagnosis and monitoring in engineering applications.

3. SUGGESTED METHODOLOGY

The methodology elaborated in this paper concerns a) the description of a suitable pre-processing technique for the acquired dataset and b) the development of a self-learning model that can estimate whether a given data point corresponds to a reference (nominal) condition considered during training. As such, a self-learning model can be trained without the need of obtaining data corresponding to faulty conditions. A visual representation of the suggest methodology is presented in Fig. 1.

A number of performance measurements related to Main Engine operation are used as input. These are depicted in Table 1. Additionally, engine MCR and vessel speed were taken into consideration. This permits the development of a model that performs accurately in varying operating conditions.

Table 1: Performance measurements utilised as input for model training.

Component	Measurement description
Cylinder 1-8	Exhaust Gas Outlet Temperature
	Scavenging Air Temperature
	Jacket C.F.W. Outlet Temperature
Thrust Bearing	L.O. Outlet Temperature
Fore Camshaft Bearing	Temperature
Scavenging Air Manifold	Pressure
Air Cooler	C.W. Inlet Pressure
Fuel Oil	Inlet Pressure
	Inlet Temperature
Cylinder Jacket	C.F.W. Inlet Pressure
Turbocharger	L.O. Inlet Pressure
Piston	Cooling Oil Inlet Pressure
Lube Oil	Inlet Pressure
	Inlet Temperature

3.1 DATA PRE-PROCESSING

Acquired datasets need to be pre-processed before being used for model training so that any erroneous or missing measurements are rectified. Data pre-processing is currently a hot topic in data mining and predictive analytics, with cutting edge research focusing on optimisation and automatisation of pre-processing.

In cases of smaller, manually acquired datasets, an alternative pre-processing is performed using visual red-flags. Such red flags are elaborated in [23] and summarised in Table 2.

Methods for imputing missing or erroneous data points are described in [23, 24]. A straight-forward approach, especially valid when large datasets are available, is to completely discard any instance that contains missing features. Alternatively, any missing feature can be replaced by the mean or mode (i.e. most commonly found) value of that feature, taking into consideration the whole dataset. Besides, a regression model can be trained using the remaining data points as training and then use known instance features as input so that missing features are estimated as model output.

Table 2. Examples of data pre-processing red flags [23].

Problems	Metadata	Examples/Heuristics
Illegal values	Cardinality	e.g., cardinality (gender) > 2 indicates problem
	Max, min	Max, min should not be outside permissible range
	Variance, deviation	Variance, deviation of statistical values should not be higher than threshold
Misspellings	Feature values	Sorting on values often brings misspelled values next to correct values

3.2 DIMENSIONALITY REDUCTION

Different performance measurement variables are usually correlated. This undesirably augments model's complexity. At the same time, increases the number of data points required for training as the number of data points should exceed the number of features [16, 17]. In order to facilitate model training, dimensionality reduction techniques such as Principal Component Analysis (PCA) are applied [18, 19].

PCA provides the orthogonal transformation of possibly correlated variables into a set of linearly uncorrelated ones (principal components). To perform PCA on a given dataset, the following steps are required [21]:

- The mean of each data dimension is calculated and subtracted from the original dataset to obtain the adjusted dataset.
- The dataset's covariance matrix is calculated.
- Eigenvalues and unit eigenvectors of the covariance matrix are calculated.
- Eigenvectors are sorted by eigenvalue, highest to lowest. A number n of features is selected based on the explained variance – complexity trade-off and a feature vector is obtained by combining the first n eigenvectors.
- The post-PCA dataset matrix is obtained by multiplying the transpose of the feature vector by the transpose of the adjusted dataset matrix.

By only retaining a few features, the dimensionality of the modelling is reduced providing a basis for better results given a limited number of samples n. Nevertheless, at the same time there exists the inherent trade-off where some variance from the dataset is lost.

As such, an optimal number of principal components should be selected so that most of the dataset's variance remains explained while the total number of features is reduced.

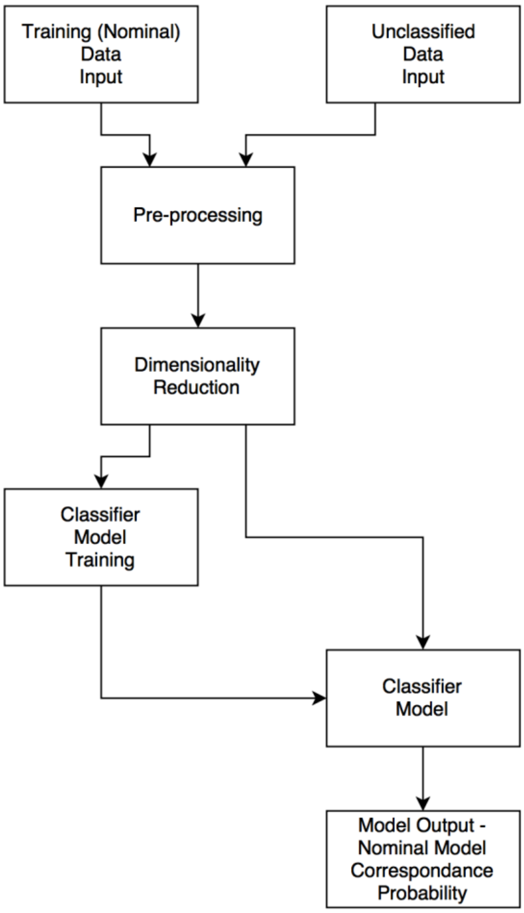

Figure 1: Methodology visual representation

3.3 MODEL TRAINING

Once certain features are obtained through PCA, these features are used as input for model training. Model in this case is a classifier that returns as output the probability that a given data point corresponds to the reference (nominal) dataset used for training. Using a training dataset that is representative of typical vessel operation and that is spanning different operational profiles, this classifier can identify abnormal patterns.

Most common self-learning classifiers are based on Neural Networks (NN), Support Vector Machines (SVM) and Decision Trees.

Compared to other pertinent algorithms, SVM is the most suitable when treating small datasets [13]. SVMs are based on Structural Risk Minimisation (SRM) that leads to balancing model complexity against overfitting [22]. Another advantage is that any optimisation minimum achieved through SVM will be a global minimum, something that is not necessarily true when treating NN minima.

Traditionally, SVMs aim to classify a dataset used as input into two of more classes. This is done by developing a separating hyperplane that can classify input data into different classes. This can either be done linearly or through a non-linear kernel function. In the case of non-linear kernel functions, input data are mapped to a high-dimensional feature-space where linear classification is possible.

In the case of the described methodology, one-class training is used. There, the dataset used for training is considered part of the single class and a small number of measurements (typically in the range of 5%) are classified as outliers to define the boundaries of the class. This algorithm builds a model where for each set of points used as input, a number in the 0-1 range is output. This number expresses the probability of the set of points corresponding to the defined class.

The exact mathematical formulation of SVM is not elaborated in this paper but the reader can refer to either Vapnik's seminal work [22] or any book in Data Mining, e.g. [21].

4. METHODOLOGY APPLICATION

In this section, four case studies are presented. Each case study performs a sensitivity analysis by considering an abnormal measurement that corresponds to a specific machine component and evaluating the model results. The dataset used for these applications was acquired on board a 4500 TEU containership as part of EU FP7 INCASS (Inspection Capabilities for Enhanced Ship Safety) Project measuring campaign [15]. Measurements were obtained hourly during a two-day period. During that time, vessel was super slow steaming with a relatively constant speed of approximately 11.5 knots, corresponding to 12% of engine MCR (Maximum Continuous Rating) point. As the dataset used was manually acquired with no missing values and no sensor malfunctions, no pre-processing was required.

4.1 CASE STUDY I (CAMSHAFT BEARING TEMPERATURE)

This case study evaluates the performance of the developed model by increasing the camshaft bearing temperature that is used as one of the algorithm inputs while maintaining all other variables in their original range. As such, while the reference (nominal) dataset has an average camshaft bearing temperature of 46 °C, gradually increasing temperatures of up to 92 °C are used as input.

4.2 CASE STUDY 2 (M/E CYL #1 EXHAUST GAS TEMPERATURE)

Following the case study set up described above, this second case study varies the temperature of the exhaust gas of a selected cylinder. The reference (nominal) dataset has an average temperature of 260 °C for the exhaust gases of this cylinder. Temperatures are gradually increased up to 520 °C and model results are evaluated.

4.3 CASE STUDY 3 (M/E LUBE OIL INLET TEMPERATURE)

In this third case study, lube oil inlet temperature is varied as part of the performed sensitivity analysis. The reference (nominal) dataset has an average temperature of 45 °C. Temperatures are gradually increased up to 58 °C and model results are again evaluated.

4.4 CASE STUDY 4 (M/E FUEL OIL INLET TEMPERATURE)

In this final case study, fuel oil inlet temperature is varied as part of the performed sensitivity analysis. The reference (nominal) dataset has an average temperature of 137 °C. Temperatures are gradually increased up to 178 °C and model results are again evaluated.

5. RESULTS

This section presents and discusses the results obtained through the case studies described above, in Section 4. Results of all case studies are visualized, showing the algorithm output for different average input measurements. Additionally, upper acceptable limit and alarm threshold values are depicted for each component, as provided by OEM.

Overall results obtained follow OEM recommendations. In some cases, the algorithm seems to be too aggressive, offering a probability drop inside the acceptable range. That can be attributed to the inherent algorithm function: estimating the probability of a measurement corresponding to a reference condition. As the training dataset in the case of these case studies only considers a very narrow, super-slow steaming operational profile, any measurements beyond that (albeit acceptable overall) do not match this profile. Additionally, whereas OEM values reflect overall limits that are not revised depending on machinery operating profile, algorithm output takes that into consideration.

5.1 CASE STUDY I (CAMSHAFT BEARING TEMPERATURE)

In this case study, model performance in varying camshaft bearing temperatures was evaluated. As camshaft bearings offer no redundancies, accurate monitoring of condition is crucial for same operation of vessel. The model accurately returns a probability drop as temperature increases (Fig. 2). A value of around 35% is returned at the OEM upper acceptable level, with 15% returned at the OEM alarm threshold. This demonstrates algorithm's ability to attribute lower correspondence probabilities as unclassified input data starts to diverge from the data used for training. In general, these probabilities can be converted into binary classification using a suitable sigmoid function [21]. In that case, probabilities over 50% will be given value 1, denoting an input dataset with a high similarity to the nominal one, and probabilities below 50% will be given value 0, denoting substantial disparities between the two datasets.

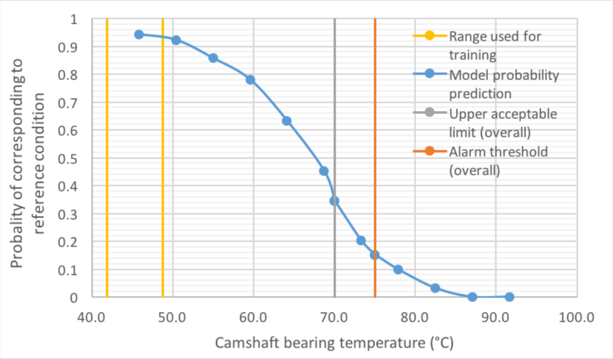

Figure 2: Camshaft bearing temperature sensitivity analysis

5.2 CASE STUDY 2 (M/E CYL #1 EXHAUST GAS TEMPERATURE)

In this case study, model performance in varying exhaust gas temperatures of a specific cylinder is evaluated. Input for all other cylinders is retained nominal. In this case, low values of 5-10% are returned for OEM acceptable limit and alarm threshold (Fig. 3). However, there exists a significant drop inside acceptable range. This can be attributed to the limited training dataset. Additionally, as noted above provided limits concern overall values while for this case study, the ship is super-slow steaming. Furthermore, in this case cylinders #2-#8 retain nominal exhaust gas temperature values. As such, a disparity, not present in training dataset, appears.

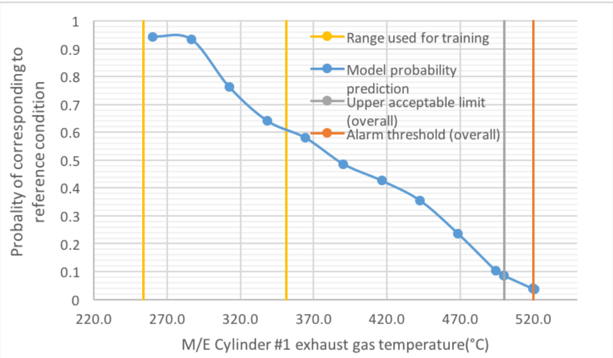

Figure 3: M/E Cylinder #1 exhaust gas temperature sensitivity analysis

5.3 CASE STUDY 3 (M/E LUBE OIL INLET TEMPERATURE)

This case study evaluates model performance in varying lube oil inlet temperatures. This component is peculiar in the sense that there exist both an upper and a lower acceptable limit. The nominal dataset included values in the whole acceptable range. As such, the model performs well, with a steady drop beyond acceptable range limits and with a probability of 30% at alarm threshold (Fig. 4).

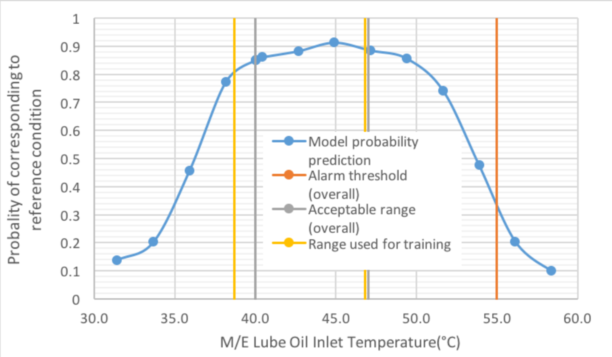

Figure 4: M/E lube oil inlet temperature sensitivity analysis

5.4 CASE STUDY 4 (M/E FUEL OIL INLET TEMPERATURE)

This case study evaluates model performance in varying fuel oil inlet temperatures. This does not reflect a possible M/E fault per se but demonstrates framework's performance when measurements of multiple subsystems are combined. This is valuable in identifying the root cause of malfunctions at system level. As with case study 3, there exist both a lower and a higher temperature threshold. Acquired values used for training span the bulk of acceptable range and values beyond limits are accurately identified as non-nominal (Fig. 5).

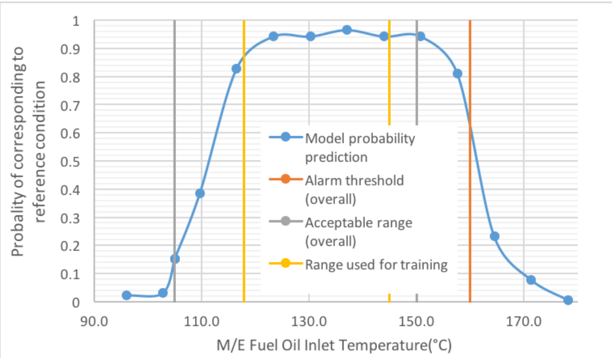

Figure 5: M/E fuel oil inlet temperature sensitivity analysis

6. CONCLUSIONS

This paper aims to present an initial framework for the processing of performance data to monitor the condition of ship machinery. First, an overview of the current state of research in the field of maritime maintenance and condition monitoring was provided. Then, proposed methodology was elaborated and showcased through several case studies. These case studies showcased the model performance while simulating faults in different subsystems.

In conclusion, future research steps include model training using a bigger, more comprehensive dataset. Besides, the development and implementation of a Decision Support System providing guidance with regards to the selection of optimal maintenance actions is proposed. Additionally, the use of vibration alongside performance measurements will be considered so that a more robust model is obtained.

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