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Oil condition monitoring of gears onboard ships using a regression approach for multivariate T^2 control charts

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ABSTRACT

In this paper, we present an oil condition and wear debris evaluation method for ship thruster gears using T^2 statistics to form control charts from a multi-sensor platform. The proposed method takes into account the different ambient conditions by multiple linear regression on the mean value as substitution from the normal empirical mean value. This regression approach accounts for the bias imposed on the empirical mean value due to different geographical and seasonal differences on the multi-sensor inputs.

Data from a gearbox are used to evaluate the length of the run-in period in order to ensure only quasi-stationary data are included in phase I of the T^2 statistics. Data from two thruster gears onboard two different ships are presented and analyzed, and the selection of the phase I data size is discussed.

A graphic overview for quick localization of T^2 signaling is also demonstrated using spider plots.

Finally, progression and trending of the T^2 statistics are investigated using orthogonal polynomials for a fix-sized data window.

1. Introduction

Evaluation of oil condition and wear debris quantity for any operating oil wetted machinery requires knowledge on the normal level for oil parameters as well as normal level for wear debris quantity and wear debris distribution.

Oil condition and wear debris quantity both relate to the condition of the oil lubricated equipment. However, the cause-effect is not straightforward. Degraded oil might accelerate equipment wear and thereby increase wear debris quantity, or an increased wear debris quantity accelerate the degradation of the oil. Both, however, are known to influence the lifetime of the oil lubricated machinery, as investigated on bearing lifetime combined with particle contamination by Sayles and Macpherson [1], on bearing damages with different lubrication conditions by Halme and and Andersson [2], on the effect of degraded gear oil on scuffing and pitting by Tuszynski et al. [3] and viscosity impact on particle (pitting) generation by Druet et al. [4]. A model taking the historic operational patterns into account could be used to evaluate a change in oil condition and wear debris quantity from a normal level. One such model has been proposed by Hotelling [5] as a generalization of the Students ratio,

$$T^2 = (\mathbf{X}-\hat{\mu})^{\mathsf{T}}\hat{\boldsymbol{\Sigma}}^{-1}(\mathbf{X}-\hat{\mu}), \qquad (1)$$

where $\mathbf{X}$ is the data vector, $\hat{\mu}$ the empirical mean vector of the data and Σ^{-1} the inverse of the empirical covariance matrix and T^2 an univariate control parameter.

The Hotelling T^2 model is commonly used in multivariate statistical process monitoring, as described in detail by Zhang et al. [6].

Such a T^2 model would enable a theoretical basis for all kinds of thruster gears, regardless of type and manufacturer. The proposed T^2 model could be used as assessment towards marine classification society regulations, prior to normal overhauls as well as overall condition monitoring. The benefit of the models simplicity (works for equipment where a stable historic operational patterns can be established) and dynamics (takes into account sensor–sensor correlations) combined with the possibility of merging oil and wear

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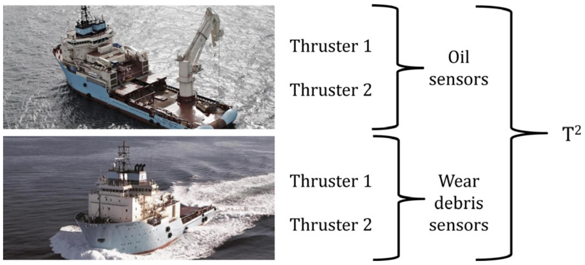

Fig. 1. Overview of model implementation. From top to bottom: Ship 1, Mærsk Achiever and ship 2, Mærsk Assister. Azimuth thruster (thruster 1) and stern thruster (thruster 2) are monitored for both ships. Reprinted with permission from Mærsk Supply Service.

model to one equivalent T^2 model could simplify warning detection for oil lubricated equipment.

We present an implementation of a model from Eq. (1), as illustrated in Fig. 1. In this paper, a T^2 model is investigated for oil condition and wear debris monitoring using oil sensors and wear debris sensors respectively for each thruster onboard each ship.

Constructing a T^2 model requires a historical data set: Phase I period of in-control data. Such data should be selected after the run-in period of the equipment where it reaches a quasi-stationary regime, as explained in Section 2.

Ambient conditions (air and sea temperature, wind, etc.) as well as operational patterns (equipment load, cooling efficiency, etc.) are expected to bias the empirical mean value of the oil condition sensors, as investigated by Soleimani et al. [7], and to a less extent, the empirical mean value of the wear debris sensors due to viscosity change of the oil. We propose a multiple linear regression on the empirical mean value of the sensors' data to account for the bias, as explained in Section 3.

Construction of the phase I chart as well as selecting an appropriate time interval are described in Section 4.

The T^2 models for phase II (monitoring) and a graphic spider plot overview for quick assessment are presented in Section 5. Orthogonal polynomial models for estimation of system trending and progression are implemented in Section 6.

Discussion of the presented models and conclusion are found in Sections 7 and 8, respectively.

2. Methodology

The T^2 model from Eq. (1) can be constructed empirically with a data set from a quasi-stationary regime (phase I) in order to calculate the empirical mean value, $\hat{\mu}$, construct the covariance matrix, Σ, and determine the upper control limit (UCL) from the distribution.

A control model (phase II) can be constructed using the known mean value, covariance matrix and new data.

Data is analysed and plotted using MatLab® software.

2.1. Oil condition and sensors – Phase I

Oil quality in oil analysis refers relative to the virgin oil quality before introduced in a lubrication system. Oil sample reference measurements normally include inductively coupled plasma mass spectroscopy (ICP-MS) for element analysis [8], viscosity analysis [9], titration for acid level determination [10] and water content [11], oxidation stability by rotating pressure vessel oxidation test (RPVOT) [12] and spectral analysis by Fourier Transform Infra Red spectroscopy (FTIR) [13].

Correlation of oil quality for oil-sample analysis with electrical impedance spectroscopy (EIS) has been investigated by Lizhi et al. [14]. Such EIS like sensors are implemented in the multi-sensor platform installed on the ships investigated in this work.

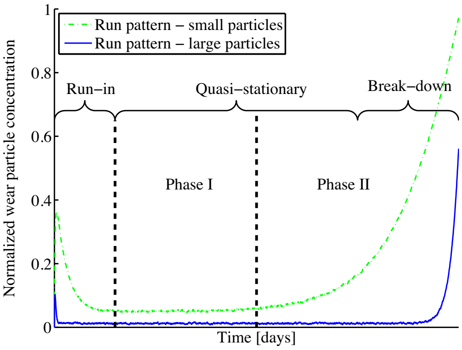

Fig. 2. Run-in, phase I and phase II selection compared with equipment life cycle. Figure modified from [17].

The oil parameters: conductivity, permittivity, relative humidity and viscosity are used to assess the oil quality, and it is expected that the relative change in conductivity, permittivity and viscosity of a system, in a quasi-stationary regime, does not change rapidly with time. Measurement of the relative humidity in the oil is included, since it has been shown by Bulletin [15] and Troyer [16] that the water contents both affect the oil oxidation rate and oil quality. The phase I period for the oil condition monitoring should be chosen from a period of time close to the introduction of the virgin oil to the lubrication system.

2.2. Wear debris and sensors – Phase I

The wear debris quantity, during the life cycle of an equipment, displays a bath-tub curve shape as simulated in Henneberg et al. [17], where run-in time depends on the wear debris particle size observed.

The sensors used in monitoring the wear debris quantity are similar to the ones described in Tic et al. [18] and Li and Zhe [19]. Small wear debris particles (4 μm to approximately 200 μm) are measured by an optical particle sensor, and larger ferrous wear debris particles (50 μm to approximately 1000 μm) are measured by an inductive particle sensor.

Regardless of wear debris size, run-in data, as seen in Fig. 2, are excluded from the phase I historical data set in order to optimize the T^2 model in phase II to detect changes from the quasi-stationary regime.

Run-in of a gear has been investigated by Link et al. [20] concluding that no fixed time period of run-in exists today (year 2011).

Wear debris data from a 6 MW gearbox suggest a run-in time exceeding 400 h when observing the wear debris particles larger than 4 μm, see Fig. 3. The wear debris sensor is similar to the one used in the multi-sensor platform. In order to ensure a quasi-stationary regime for phase I data selection, a time period of 1200 h (a safety factor of 3 is used since equipment and gear are different) is chosen for the T^2 model presented in this work.

Observations in the thruster data after the chosen run-in period show a bias shift in the mean value according to equipment operation, load and ambient conditions. Applying multiple linear regression for the estimating the empirical mean value is therefore used in order to minimize the bias shift.

3. Mean value model by multiple linear regression

The ambient conditions of the ships and the operational load levels of the thrusters, as described in Section 1, influence the general