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From anomaly detection to root cause analysis: a novel maritime maintenance framework using digital twin synthetic dataset

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From anomaly detection to root cause analysis: a novel maritime maintenance framework using digital twin synthetic dataset

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Abstract. This paper presents a novel approach in the context of condition-based maintenance (CBM) in the maritime sector, leveraging unsupervised learning through Long Short-Term Memory (LSTM) networks. As ships transition toward unmanned operations, the traditional approach of scheduled maintenance becomes inadequate. CBM leverages advanced sensor networks, real-time monitoring systems, and predictive analytics to enable proactive maintenance strategies without human presence onboard. The research carried out in this paper aims to develop a methodology that combines anomaly detection with feature contribution analysis to identify the presence of anomalies and determine which system parameter signals are most responsible for anomalous behaviour. The approach is validated using a marine gearbox digital twin that generates synthetic operational data. In particular, the adopted model focuses on kinematic parameters such as torque and temperature. Moreover, the digital twin enables the simulation of both step changes and continuous degradation patterns to emulate an anomaly. A key innovation lies in the integration of contribution analysis within the LSTM framework, providing deeper insights into fault progression. Moreover, by using synthetic data with known anomaly patterns, the methodology demonstrates the ability to correctly identify the features most responsible for reconstruction error. This capability is particularly significant for real-world maritime applications, where the critical parameters driving system degradation are typically unknown beforehand and must be discovered through analysis. The framework addresses the common challenge of scarce run-to-failure data in maritime maintenance by adopting a fully data-driven, unsupervised approach where failure characteristics are not pre-defined. The methodology encompasses data generation through digital twin simulation, data processing, Health Index (HI) construction, and predictive analysis. The results validate the effectiveness of this integrated approach in both identifying potential failures and their root causes, enabling more informed maintenance planning in maritime applications. Indeed, the validation approach utilizes synthetic data generated through a digital twin to address the scarcity of real-world run-to-failure data in maritime applications.

1. Introduction

The past ten years have witnessed the importance of a transformative technological period. Consequently, research dedicated to developing autonomous vehicles has experienced significant growth across all industrial domains. This research momentum became feasible through substantial technological advancements that have occurred in recent years and continue to develop. The modern Information and Communications Technology (ICT) industry has made possible solutions that have fundamentally reshaped vehicle architecture, enabling manufacturers to integrate advanced capabilities and enhance current functionality through reduced costs and improved accessibility of technology.

Although historically conservative regarding rapid technological shifts, the maritime industry has experienced profound transformation within this landscape of major technological progress, driven by potential advantages including enhanced fuel efficiency, reduced operational expenses, and improved onboard safety systems. This evolution has generated various terminology related to enhanced automation, including autonomous surface vehicles (ASV), unmanned surface vehicles (USV), and maritime autonomous surface ships (MASS), terms that are frequently confused when describing different vessel capabilities.

A vessel equipped with advanced automation capabilities such as remote navigation systems, collision prevention technology, or decision-making support systems is designated as a "smart ship." The "Global Marine Technology Trends 2030" report [1] identified "smart ships" as a crucial development element for the maritime industry, particularly for significantly enhancing navigational safety. Subsequently, following the Maritime Safety Committee's (MSC) 98th session in February 2017, the International Maritime Organization (IMO) initiated efforts to establish a regulatory framework governing MASS operations and their integration with crewed vessels under existing IMO regulations [2].

However, the size of the vessel is only one of the factors to be considered, along with the specific operations the vessel must perform and the degree to which the crew is involved in performing tasks of varying complexity. For example, fishing vessels require crew members to perform numerous tasks that may prove too intricate for automated systems to replicate [3]. Indeed, eliminating crew members presents considerable challenges, particularly for service and fishing vessels. Furthermore, the concept that achieving fully autonomous navigation may be restricted to smaller vessels where crew functions can be easily automated finds support from Maersk CEO Søren Skou [4].

The maintenance intervention sector will undergo profound transformations within this context of advancing toward unmanned operations. When onboard personnel are removed or relocated to shore-based control centers, vessel operability must be guaranteed and critical systems require continuous monitoring to assess their health status and potentially schedule restoration interventions while minimizing operational disruption through condition-based maintenance (CBM) approaches [5].

The research presented operates within this framework and aims to propose an innovative strategy that combines anomaly detection techniques with feature contribution analysis, enabling root cause analysis tasks without relying on knowledge-based approaches.

Specifically, the approach employed is based on unsupervised learning through Long Short-Term Memory (LSTM) neural networks [6], constructed in autoencoder architectures [7], a structure particularly well-suited for managing and processing time series data. The available data are processed through the LSTM autoencoder, which learns normal operational patterns to calculate reconstruction error for anomaly detection [8] and the Health Index (HI), which

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provides real-time assessment of the degradation state of the entire system or individual components based on the considered signal pool.

A particularly innovative aspect lies in the integration of feature contribution analysis, thereby enabling a deeper understanding of the underlying causes leading to abnormal values, thanks to feature contribution methodology facilitates not only the identification of system anomalies but also the determination of components most responsible for generating such anomalies.

The developed methodology implements both individual signal analysis, training separate models for each signal-power pair, and a combined model capable of considering all system components simultaneously.

This approach enables not only anomaly detection but also quantification of each component's percentage contribution to the overall system reconstruction error, providing direct indication of potential malfunction causes. This research represents the evolution of existing CBM systems developed by Fincantieri NexTech, which currently employs traditional statistical approaches [9], toward advanced machine learning methodologies that provide enhanced diagnostic capabilities and interpretability for autonomous maritime operations.

A fundamental step in validating this methodology involved utilizing synthetic datasets generated through digital twin simulations [10] of a marine gearbox. Indeed, a key challenge in maritime CBM research is the scarcity of real-world run-to-failure data, as allowing complex maritime systems to fail completely during operation presents significant safety and economic risks. This limitation is particularly pronounced for non-industrial research entities, necessitating innovative approaches such as digital twin-based synthetic data generation.

In detail, three distinct datasets were created: one representing normal operational conditions, one featuring step-function anomalies, and one containing time-dependent anomalies. This approach provided complete control over the analyzed data, with prior knowledge of anomaly onset, temporal evolution, and underlying causes.

The utilization of synthetic data with known anomaly patterns enables accurate identification of primary components responsible for failures. This contribution holds particular significance when parameters leading to system degradation are unknown a priori and must be discovered through received data analysis.

The complete pipeline encompasses synthetic data generation through numerical simulations of the gearbox digital twin, autoencoder modeling and network hyperparameter optimization for individual signals and signal pools to construct reference models during training phase, anomaly detection tasks based on reconstruction error with corresponding HI construction, and detailed feature contribution analysis. Additionally, the system provides health status visualization through traffic-light categorization of system health states to facilitate interpretation by human operators.

Eventually, an additional aspect addressed involves anomaly prediction tasks, where anomalies can be forecasted before their occurrence. In this case, Remaining Useful Life (RUL) estimation was performed without relying on run-to-failure data, as such information is typically unavailable [11]. The absence of RUL estimation for individual components is due to the lack of historical failure data, which could help in estimation through analysis of recurrent patterns or reconstruction values leading to failures.

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2. Gearbox - Digital twining

The digital twin is a technology that can be effectively used to design and implement new asset monitoring strategies as well to simulate asset operational availability during future missions. Indeed, simulation allows the study of either the performance and trends of vessels [12] or to develop autonomous/similar systems [13, 14].

In the present paper the digital twin of a ship gearbox has been used to generate synthetic (simulated) data used to design and train the gearbox health assessment and prediction.

The digital twin methodology is based on the assumption that the digital replica of the physical asset is able to provide output with the required fidelity.

This aspect is often a ‘chicken and egg’ problem that can be increasing fidelity step by step during development [15]. The topic of the presented work is a gearbox health assessment algorithm based on continuous monitoring of lubricating oil temperature. The gearbox is part of a complex propulsion system for a front-line naval ship, designed to operate worldwide. The digital twin of the ship propulsion plant was developed during the ship design and tested during early ship operation [16].

However, the oil temperature behaviour was not part of the original modelling phase, it has been added to support the development of the health assessment module.

2.1 Oil temperature modeling

The oil temperature model is based on a mathematical model of the gearbox based on main physical principles. The gearbox consists of two trains of helical meshes, each one providing a constant gear ratio. Each mesh contact is oil lubricated, and each gear train is supported by two oil lubricated journal bearings. The model input is the engine power (torque and revolution), while the model outputs are the propeller power (torque and revolution) and the temperatures in all bearings. The oil temperature increase in a journal bearing is modeled by the following equations:

$$\Delta T = \frac{P_d}{\rho \cdot c \cdot Q_Z}\ [°C] \tag{1}$$

$$Q_Z = Q_{Zrel} \cdot \mathrm{b} \cdot \frac{s}{2} \cdot \omega \cdot \frac{d_L}{2}\ \left[\frac{m^3}{s}\right] \tag{2}$$

$$P_d = \mu \cdot F \cdot \frac{d_L}{2} \cdot \omega\ \ [W] \tag{3}$$

where: Pd is the friction power loss in $[W]$, ρ is the oil density in $[\frac{kg}{m^3}]$, c is the oil thermal capacity in $[\frac{J}{kg\,K}]$, Qz is the oil flow rate in $[\frac{m^3}{s}]$, s is the bearing clearance $[m]$, dL is the nominal journal diameter $[m]$, F is the bearing load in $[N]$, μ is a friction efficiency in [-].

The bearing load is derived by the teeth force of each gear mesh; the latter is computed by using the input power, the pinion and the wheel diameters.

In general, in a ship propulsion plant the instantaneous power is more related to ship speed, rudder angle and sea state through the hydrodynamic equations coupled with the engine and control equations. The full description of the ship propulsion model and its validation with full scale measurements is reported in [17].

Figure 1 shows the schematic representation of the modelling tool developed in MATLAB/Simulink environment using Functional Mock-up Unit (FMU) technique to support code sharing.

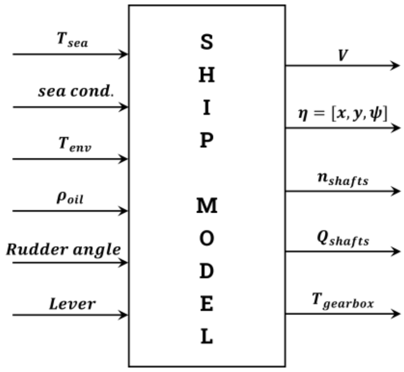

Figure 1-Digital twin input-output schematic

The code has been designed to simulate a mission defined by the relationship ship speed-time (telegraph lever-time). This capability has been extended to simulate one-year operation or multiple-year operations using the random walk concept described in the following section. This has been made in order to enable the creation of a dataset for training and testing purposes.

2.2 Operational profile simulation

Simulations can play a crucial role in forecasting the long-term behaviour of a ship's propulsion system under varying operating conditions. The ship Operational profile represents the distribution of the ship speed over one year operation. The distribution (normal, uniform, etc..) is defined in the ship design specifications.

The operational simulation has the objective to represent the random variation of the ship speed during the year, given that the speed distribution overall is represented by the distribution defined in the specification.

The technique used in this work is the Markov Chain Monte Carlo (MCMC), a method that enables to draw samples from a given distribution. The MCMC has been used to draw a sample of 2500 values, representing the telegraph lever positions over one year of operation (2500 hours). Each telegraph lever value has been used as input of the ship simulator for a time lap of 3600 seconds, repeating this technique for all telegraph lever values, enables to simulate one year operation with a defined speed distribution. Indeed, the MCMC technique enables drawing samples from given distributions while introducing realistic operational variability that reflects actual maritime operations, including speed variations, environmental influences, and operational decisions.

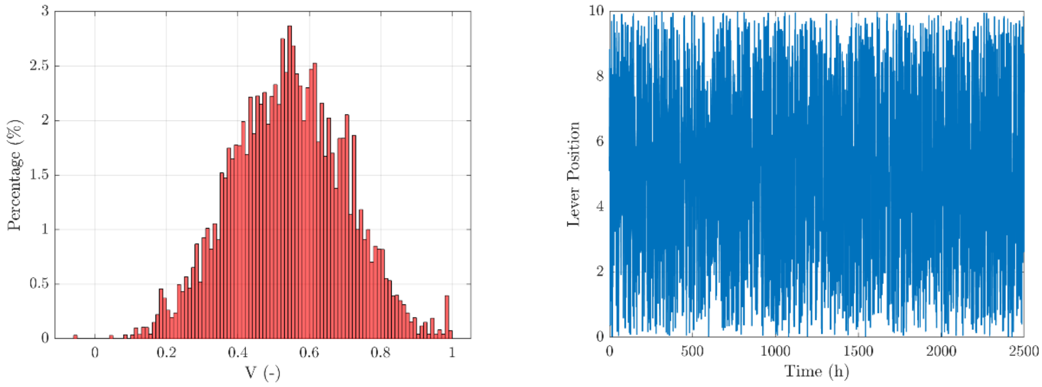

Figure 2 - Ship operational profile by random walk

Figure 2(left) shows the speed distribution as resulted from the MCMC sampling with 2500 samples, and Figure 2 (right) shows the corresponding sequence of telegraph lever command used to run the simulation. In the given example the ship's speed follows a Gaussian distribution with mean 0.5 (where 1 represents the maximum speed),

2.3 Training dataset

The dataset is represented by the feature available in the output of the simulator, as shown in Figure 1. The dataset contains the following features: time, input_telegraphSTBD, input_telegraphPORT, input_rudderSTBD, input_rudderPORT, V_ship, ENGINE_torque, STBDshaft_torque, PORTshaft_torque, ENGINE_rpm, PORTshaft_rpm, STBDshaft_rpm, deltaT_firstreduction_wheel, deltaT_secondreduction_pinion, deltaT_secondreduction_wheel.

In this work only the oil temperature analysis is discussed (deltaT). The training dataset is represented by the simulation of one year operation with the ship as good as new. In particular, the gearbox parameters have been assumed at their nominal design value without any variation respect it. Two kinds of training datasets have been produced, one simulating a gaussian speed distribution and one simulating a uniform distribution of ship speed (Figure 3).

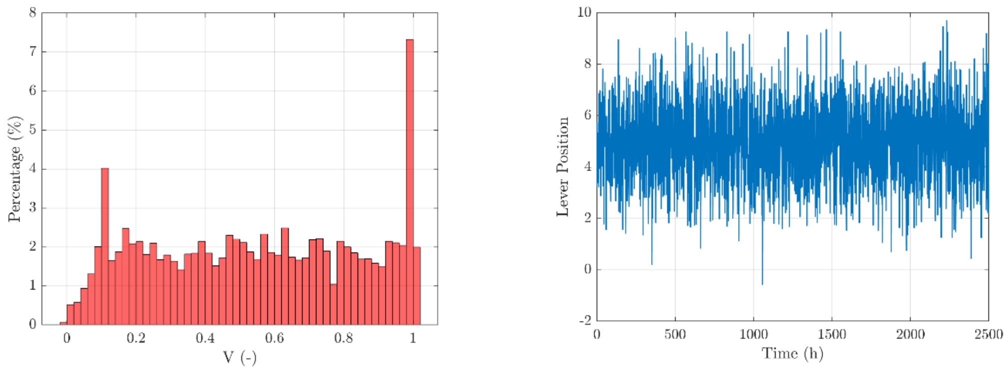

Figure 3 - Ship operational profile with uniform distribution

2.4 Dataset with anomalies

Several dataset simulating anomalies have been produced. The simulated anomaly is the oil density variation. The oil density is responsible for proper lubrication, and the system is designed with threshold oil temperature based on nominal oil density. A change in density can trigger a change in lubricating effectiveness and ultimately in oil temperature behaviour.

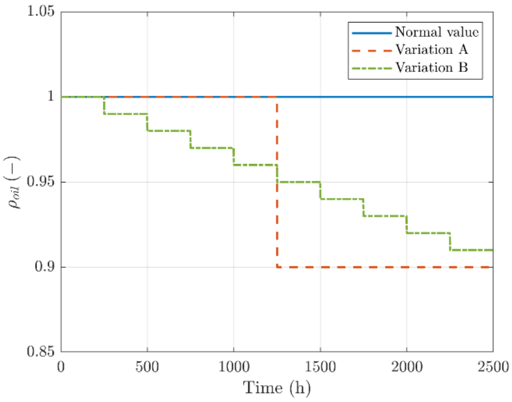

Figure 4 - Oil density variation (anomaly)

Two different anomalies have been modelled: a step change and a progressive degradation, as shown in Figure 4. Indeed, a total of 4 anomaly dataset have been produced: normal distribution with step change and with progressive change, uniform distribution with step change and with progressive change.

3. Methodology

The methodology encompasses a comprehensive framework for anomaly detection and health index evaluation designed to address the challenges of maritime maintenance in autonomous operations.

The LSTM autoencoder framework employs a generic design applicable to multiple failure modes beyond oil density variations. The cornerstone is training on correct working datasets, making the approach adaptable to various systems and failure scenarios.

Moreover, the feature contribution analysis identifies any deviating parameter regardless of failure type. The key challenge is the trained network's sensitivity to well-functioning data, as actual device breaking limits cannot be determined without historical failure data.

3.1 Data Acquisition and Preprocessing

The initial phase focuses on acquiring time series data from operational equipment. These time series can be divided into two main categories e.g. primary and secondary signals. The primary signal represents the output of the device and represents the working state of the devices. The secondary signals can be all the other signals bounded to the primary one. This data undergoes pre-processing to ensure quality and suitability for model training, including:

- the normalization of the data acquired to scale them in a uniform range [0;1] for consistent model performance;
- the creation of sequences for structuring data for the LSTM processing;
- the validation of the quality of data through statistical methods to ensure data integrity and identify potential outliers or missing values;
- a feature selection in which certain features were removed from the analysis due to their limited contribution to anomaly detection accuracy and to reduce computational complexity.

At the end of this procedure a list of more meaningful features without any missing values is obtained. In this paper the primary signal is represented by the signal ‘engine_torque’, which is used as the main health indicator due to its direct relationship with the mechanical system's

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condition. Supporting temperature signals ('deltaT_firstreduction_wheel', 'deltaT_secondreduction_pinion', 'deltaT_secondreduction_wheel') provide additional diagnostic information.

3.2 LSTM Autoencoder Architecture

The core of the proposed approach is an LSTM-based autoencoder architecture designed to learn representations of normal operational patterns from sequential data. This architecture was selected because LSTM's natural ability to capture long-term dependencies in sequential data makes it especially appropriate for time series analysis.

In contrast to neural networks, LSTM cells utilize memory functions via their unique gate architecture, enabling them to preserve significant information over long periods while eliminating unimportant data- an essential characteristic for examining operational trends that can emerge over different time spans.

The model, indeed, consists of an encoder that compresses input sequences into a lower-dimensional representation, a decoder that reconstructs the original sequences from the compressed representation and a calculation of the reconstruction error that quantifies the model's ability to recreate the input, serving as the basis for anomaly detection.

The training process involves several critical steps: hyperparameter optimization, a grid search is performed to identify optimal network architecture parameters including number of LSTM layers, hidden units per layer, learning rate, batch-size and sequence length; training strategy, the model is trained exclusively on normal operational data using the Adam optimizer with early stopping to prevent overfitting, in which a validation split of 20% is used to monitor training progress and determine optimal stopping criteria.

3.3 Anomaly Detection

During the training phase, an anomaly threshold is computed by means of mean square error (MSE) corresponding to the mean of reconstruction errors from the highest 5% observed in that phase, calculated by comparing predicted output and actual values as shown in Figure 5. Through this approach, the model flags sequences that diverge significantly from the learned pattern of normal functionality, thereby identifying potential anomalies in the acquired signals, i.e. when the MSE of a given sequence exceeds this threshold.

Moreover, the max value has not selected because the training set could also be affected by some outliers. Determining the threshold is crucial in effectively distinguishing between normal and anomalous component sequences, which directly influences the accuracy and reliability of the predictive maintenance system. The threshold setting methodology balances sensitivity (identifying true anomalies) with specificity (preventing false positives).

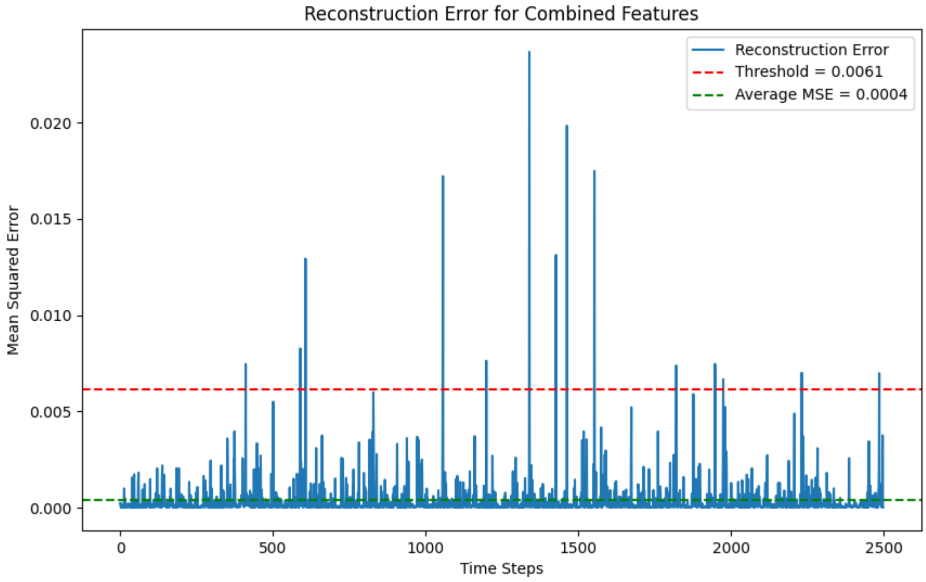

Figure 5 - MSE of training phase for multivariate model.

3.4 Health Index

Building upon the reconstruction error from the autoencoder, a Health Index (HI) was developed to quantify the operational condition of each component or the entire system, expressed as a percentage of optimal functionality. The calculation of this index follows a structured approach based on arbitrary thresholds: when the reconstruction errors fall below "threshold/3" the component is classified as "very healthy" with an HI arbitrarily set to 100%.

For reconstruction errors between "threshold/3" and the established anomaly threshold, a normalized linear scale is implemented, where the HI decreases proportionally as the reconstruction error increases. Components with an HI above 50% are classified as "moderately healthy" while those with HI values between 1% and 50% are categorised as "borderline", indicating potential degradation requiring attention. Eventually, when the reconstruction error exceeds the anomaly threshold, the HI drops to 0%, signalling an anomaly. This graduated approach enables proactive maintenance planning based on the severity of the deviation from normal operational patterns, providing maintenance personnel with clear, actionable information about system health status.

In Figure 6 the health index assessment based on the linear failure anomaly dataset has been reported, here it is possible to observe the degradation trend of HI from left to right.

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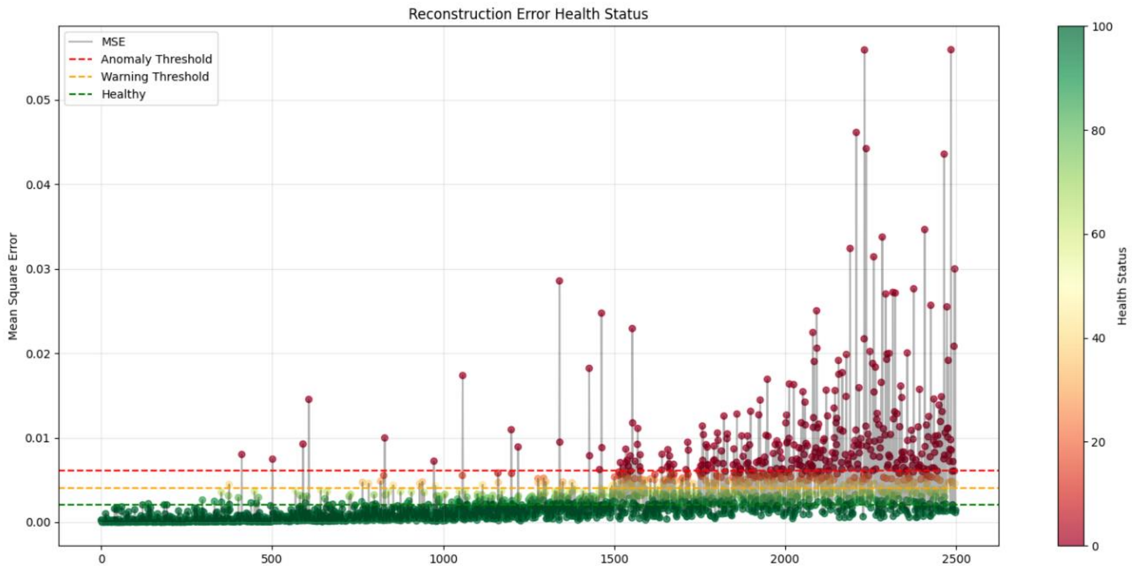

Figure 6 - HI assessment on dataset with linear anomaly

3.5 Feature Contribution Analysis

A critical component of methodology is the feature contribution analysis, which quantifies the extent to which each monitored parameter influences the occurrence of anomalies within the system. This approach enables to disaggregate the reconstruction error to identify which specific features deviate most significantly from their expected values, thereby enabling a first step data-driven analysis of root causes of system degradation.

The feature contribution analysis begins by computing the squared reconstruction error for each feature dimension at every anomaly point detected with the multivariate model. For a given anomaly at time step t, the contribution of feature i is calculated as:

$$C_i(t) = \frac{SE_i(t)}{\sum_j SE_j(t)} * 100 \tag{4}$$

where $SE_i(t)$ denotes the squared error between the actual and reconstructed values for only the feature i by using their trained model, and $\sum_j SE_j(t)$ represents the cumulative reconstruction error for all features.

By integrating anomaly detection with targeted diagnostic capabilities, this methodology transcends conventional binary classification methods that only pinpoint the presence of an anomaly without providing actionable insights into its source. Maintenance can thus carry out specifically focused actions, enhancing resource distribution and reducing equipment inactivity.

This diagnostic improvement significantly increases the practical usefulness of the system, enabling the transition from reactive maintenance strategies to predictive maintenance strategies, which are essential in an autonomous navigation scenario where operation without human intervention or with very limited intervention must be guaranteed.

Figure 7 shows what the contributions of each characteristic are after the multivariate model has identified the anomaly.

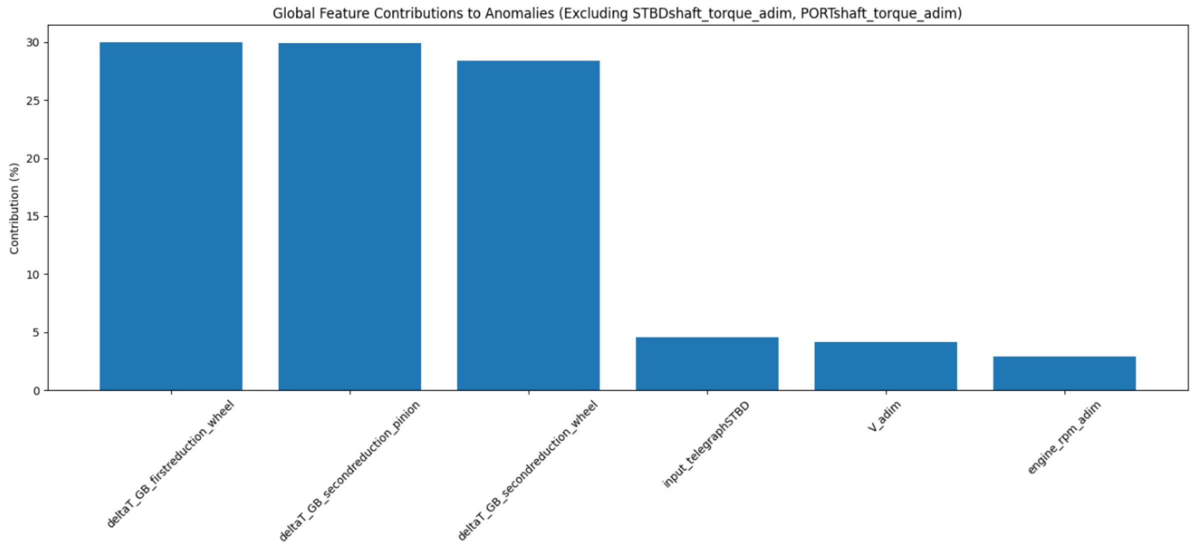

Figure 7 - Feature contribution to anomalies

3.6 Predictive Analysis and Remaining Useful Life Estimation

The framework extends beyond anomaly detection to provide predictive capabilities through Remaining Useful Life (RUL) estimation. Given the typical absence of historical run-to-failure data in maritime applications, this approach leverages the temporal evolution of reconstruction errors to forecast future anomalies.

The RUL estimation process analyzes the trend of reconstruction errors over a sliding window of recent observations, using a linear regression model fitted on declining patterns to capture the degradation trajectory. The intersection between this trend line and the anomaly threshold provides the estimated time-to-failure.

In particular as shown in Figure 8 different time windows were considered, with each point in the time series representing the aggregation of the data corresponding to 1 hour, then 3,4,5,6 and 7-day windows were considered to evaluate the difference between the different time intervals. For this case study, the results suggest that a 3-day window seems to be more unstable in predicting a correct trend while a 7-day window seems to be slow in finding potential anomalies. In this context, the 4-5 and 6-day windows find the right reference point by overcoming the reconstruction error.

It must be said that in this case it was easy to verify the goodness of the result because it was known a priori, in a real case further considerations should be made on the continuation of the anomalous case over time in order to limit the overshoots present in the figure and adopt a more dynamic policy that warns of the change in slope, a symptom of deterioration.

Eventually, this predictive capability enables proactive maintenance scheduling, allowing remote operators to plan interventions before critical failures occur, thereby minimizing operational disruptions and optimizing resource allocations.

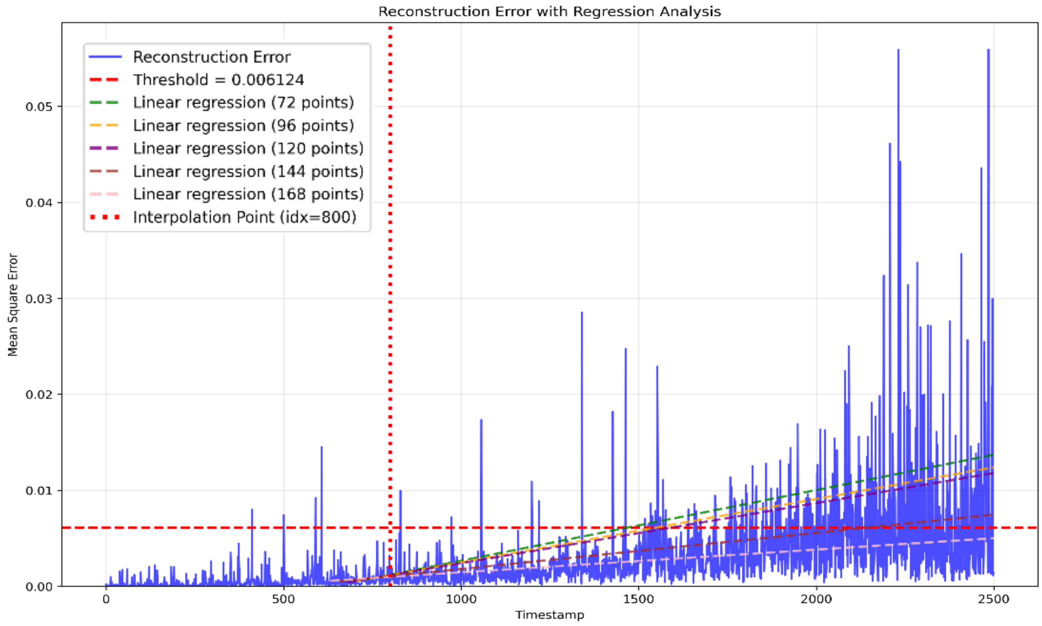

Figure 8 - RUL results on dataset with progressive anomaly

4. Results and Discussion

The methodology was validated using synthetic datasets generated through the marine gearbox digital twin: baseline normal operation and progressive degradation scenario. Each dataset comprised 2,500-time steps, each representing an hour, with engine torque as drive feature. The LSTM autoencoder successfully learned normal operation patterns during training, maintaining low and stable reconstruction errors during not anomalous operations. The model demonstrated effective detection capabilities for both abrupt and gradual anomalies. For sudden changes in system behaviour, anomaly detection occurred precise, while progressive deterioration was identified well before critical failure conditions. In addition, the Health Index provided intuitive visualization of system degradation, transitioning smoothly from healthy to anomalous states as system conditions evolved.

Moreover, the feature contribution analysis demonstrated robust diagnostic performance across different anomaly scenarios. Indeed, the approach showed consistent performance in isolating the dominant contributing factors, enabling the first step by means of a data-driven analysis for a root-cause analysis.

Eventually, the predictive analysis demonstrated promising performance in forecasting anomaly occurrences across different degradations scenarios. For progressive degradation patterns, the methodology successfully identified declining trends, providing advance warning of impending failures. The RUL estimation showed reliable performance for gradual anomalies, with prediction accuracy improving as more historical data became available for trend analysis. The linear regression approach proved adequate for the synthetic datasets, capturing the essential degradation patterns within the controlled simulation environment. However, the predictive capability could show limitations in scenarios with irregular degradation patterns. The methodology's effectiveness depends critically on the consistency of the degradation process and the quality of the underlying trend data. Current limitations include reliance on synthetic data, though this addresses maritime CBM's fundamental challenge of failure data scarcity. The single

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failure mode focus serves as proof-of-concept, with the generic methodology designed for extension to multiple failure scenarios.

In conclusion the results validate the effectiveness of LSTM autoencoders for maritime anomaly detection and health assessment. The feature contribution analysis provides actionable maintenance insights by identifying specific failure sources. However, several limitations exist: validation was conducted only on synthetic data and focuses on single failure mode (oil density). Future work should address real-world validation and implementing more sophisticated trend analysis techniques, incorporating uncertainty to provide confidence intervals for RUL predictions. While validation currently relies on synthetic data from a rigorously validated digital twin, this approach addresses the well-documented challenge of maritime failure data scarcity. The methodology's generic design enables extension beyond the current gearbox application to multiple maritime systems and failure modes. Eventually, the proposed framework has significant potential for autonomous vessel maintenance, offering unsupervised fault detection with interpretable diagnostics, which is essential for unmanned maritime operations.

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