Enhancing Predictive Maintenance in the Maritime Industry with Unsupervised Learning

N. Faggioni[*+], A. Caviglia[*], N. Guarnera[#], E. Schininà[#], E. Sansebastiano[*] & R. Chiti[*]

[*] *Fincantieri NexTech, Viale Brigate Partigiane 92R, 16129, Genoa, Italy.*
[#] *Argo IT s.r.l., Via Caterina Rossi 2/1, 16154 Genoa, Italy.*

[+] Corresponding Author. Email: nicolo.faggioni@fincantierinxt.it

Synopsis

This paper introduces a novel approach centred on unsupervised learning, specifically leveraging state-of-the-art Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM). The study aligns with the domain of predictive maintenance (PdM) and time series analysis for evaluating the health status of devices.
The proposed methodology seeks to enhance current PdM practices by integrating machine learning (ML) into the conventional statistical framework. ML techniques are increasingly applied in the industrial sector, demonstrating their capacity to capture complex correlations that may elude human operators.
Indeed, the management of scheduled maintenance in the naval sector is a complex challenge, primarily due to the diversity of devices and systems on board ships. These systems vary in nature, complexity, and criticality, making it challenging to adopt a standardized maintenance strategy.
Solutions based on Condition-Based Maintenance (CBM) aim to perform maintenance based on the actual operational conditions of a system, rather than following fixed schedules. This approach relies on the use of sensors, continuous monitoring, and advanced diagnostics to assess the health status of components and predict failure times.
However, despite advancements in this direction, there are still significant challenges to address. One of the main challenges is the heterogeneity of systems on board ships.
Furthermore, approaching the predictive maintenance task for onboard ship equipment, a key challenge emerges when attempting to estimate the Remaining Useful Life (RUL) of a component given the scarcity of run-to-failure data. For such a reason, the developed model adopts a fully data-driven approach, where the failure characteristics (run-to-failure data) of the equipment are not pre-defined.
Moreover, the framework encompasses data acquisition, data preprocessing, Health Index (HI) construction, and the prediction of remaining useful life grounded in the examination of a documented failure case related to maritime equipment. Indeed, the framework has been tested on data corresponding to an actual equipment failure, enabling a direct comparison with its application to data from normally functioning equipment without anomalies.
The presented unsupervised approach serves a dual purpose: enabling real-time detection of potential failures and facilitating trend analysis of the device's health index. This dual functionality proves valuable in estimating the projected failure period.

Keywords: Condition-Based Maintenance (CBM), Predictive Maintenance (PdM), Long Short-Term Memory, Remaining Useful Life (RUL), Run-to-failure Data.

1. Introduction

Maintenance management in the naval sector poses unique challenges due to the diversity, complexity, and criticality of onboard systems (Coraddu et al., 2015). Conventional maintenance strategies often struggle to adapt to the dynamic operational conditions and varying maintenance requirements of maritime equipment. Condition-Based Maintenance (CBM) offers a more adaptive approach, relying on sensor data, continuous monitoring, and advanced diagnostics to assess the health status of components and predict maintenance needs based on actual operational conditions (Jardine et al., 2006).

Author's Biography
Nicolò Faggioni was born in Italy in 1991. He earned a Bachelor's degree in Nautical Engineering in 2014, followed by a Master's degree in Yacht Design in 2017, and a PhD in autonomous navigation in 2022, all from the University of Genoa. Currently, he is employed at Fincantieri NexTech, where he focuses on automation and control systems for the marine sector. His primary research interests include ship propulsion plants, mathematical modelling, data analysis, and numerical simulation.
Alessandro Caviglia was born in Italy in 1990. He earned a Bachelor's degree in Computer Engineering in 2019, followed by a Master's degree in Computer Engineering: Software and Computing Platforms in 2020 from the University of Genoa. Currently, he works at Fincantieri NexTech, specializing in automation and control systems for the marine sector. His primary areas of expertise are data science, cloud computing, and digitalization.
Nicola Guarnera was born in Italy in 1990. He earned a Master degree in Automation Engineering and control of complex systems in 2019, from the University of Catania. Currently, he is employed at Argo IT s.r.l., where he focuses on research and developing Machine Learning solutions and Data analysis on industrial problems. His primary research interests include modelling plants through mathematical, statistical and data driven approaches.
Emilio Schininà was born in Italy in 1992. He holds a bachelor's degree in Computer Science and Technology from the University of Ferrara in 2016 and a master's degree in Automation Engineering and Control of Complex Systems in 2020 from the University of Catania. He has previously worked under contract at the National Institute of Nuclear Physics (INFN). Currently, he collaborates with Fincantieri Nextech and ABB Limited, Italy.
Emanuele Sansebastiano was born in Italy in 1993. He earned a Bachelor's degree in Industrial Engineering in 2015, followed by a Master's degree in Robotics (European Master on Advanced Robotics) in 2017. Currently, he is employed at Fincantieri NexTech, where he is leading the development team of the Situational Awareness System (SAS) for maritime autonomous vehicles. His primary research interests include autonomous navigation, machine learning, fast computing data forecast.
Roberto Chiti was born in Italy in 1985. He earned a Master Degree in Naval Engineering in 2011 at University of Genoa. Currently he is employed at Fincantieri NexTech with the role of Project Leader for U212NFS submarines automation, for Italian Navy. His background and research interests refer to software control and dynamic simulation of ship propulsion systems, Dynamic Positioning System and Autopilot System.

However, despite advancements in CBM and predictive maintenance methodologies, significant challenges persist. One such challenge is the estimation of the Remaining Useful Life (RUL) of components, particularly in the absence of sufficient run-to-failure data (Zhang et al., 2021). Traditional approaches often rely on predefined models and assumptions, limiting their effectiveness in accurately predicting RUL. In this context, a data-driven approach becomes crucial, leveraging the available data to develop models that can adapt to the unique characteristics of maritime equipment.

The proposed methodology encompasses a comprehensive framework for predictive maintenance, including data acquisition, preprocessing, Health Index (HI) construction, and the prediction of remaining useful life (Xia et al., 2020). By adopting an unsupervised learning approach, the framework aims to overcome the limitations of traditional methodologies and provide more accurate and reliable predictions of equipment health and failure times (Liao et al., 2018).

In this context, the predictive maintenance (PdM) has emerged as a critical strategy in industrial sectors, aiming to enhance operational efficiency, minimize downtime, and reduce maintenance costs (Wu et al., 2020). In the domain of maritime equipment, particularly in the naval sector, the reliability and performance of devices are essential to ensure the completion of task without failures. Indeed, the adoption of advanced predictive maintenance methodologies becomes crucial.

This paper introduces a new approach focusing on unsupervised learning, leveraging Recurrent Neural Networks (RNNs), particularly short-term memory (LSTM), to address the challenges inherent in predictive maintenance of marine devices (Han et al., 2021). This approach advances beyond the supervised methods by offering a more flexible and adaptable solution for maritime applications where labelled failure data is often limited.

Conventional and most widespread predictive maintenance systems are based on statistical concepts, which often are based on linear models and predefined relationships between variables. The bottleneck of these approaches is their limitations to capture complex, non-linear interactions and hidden patterns within the multidimensional data typically generated by industrial equipment not well known at priori. For instance, traditional methods might struggle to detect interdependencies between multiple sensor readings that collectively indicate an impending failure, especially when these relationships change over time or under different operating conditions.

For such a reason, ML algorithms have proven to overcome this bottleneck by demonstrating the ability to capture complex correlations and patterns in the data, thus enabling more accurate predictions of equipment health and failure times (Zhao et al., 2023). The flexibility of ML models to adapt to evolving patterns in the data also makes them particularly well-suited for handling the dynamic nature of industrial processes and equipment behaviour.

This study seeks to augment current PdM practices by harnessing the power of ML, particularly by means of time series analysis for evaluating the health status of marine devices.

Furthermore, the effectiveness of the proposed approach is evaluated through real-world application to actual equipment failure data, enabling a direct comparison with traditional statistical methods.

A detailed description of the actual methodology is reported in section 2, while the potential development by means of LSTM is shown in section 3 and the results were discussed and shown in section 4. Eventually, the conclusion and recommendations are shown in Section 6 discussing the implications of what is shown for the field of predictive maintenance in maritime applications.

1.1. Maritime scenario criticalities

In the maritime domain, predicting potential failures holds critical importance for safeguarding both personnel and assets, as well as ensuring uninterrupted operational continuity (Lazakis et al., 2017).

Indeed, proactive failure prediction plays a pivotal role in ensuring the safety of crew members and passengers. By anticipating potential failures in critical systems such as propulsion engines can implement pre-emptive measures to mitigate risks of accidents at sea, thereby preventing potential loss of life and vessel operational capability (Ivankevich et al., 2019). Moreover, failure prediction methodologies are indispensable for preventing environmental catastrophes.

Maritime accidents, such as oil spills or collisions, can have devastating consequences on marine ecosystems (Duffey & Saull, 2009). From an operational point of view, predictive maintenance is essential to avoid costly downtime; in fact, unplanned equipment failures can result in significant financial losses for shipping companies due to interrupted operations and emergency repairs (Jimenez et al., 2020).

In addition, another key aspect is the reduction of operational capacity, which is very important for the military sector where the ship must guarantee the best performance even in adverse scenarios. By accurately predicting potential failures, operators can schedule maintenance activities during planned downtime, optimising operational efficiency and reducing financial burdens (Dalzochio et al., 2023). Furthermore, failure prediction methodologies contribute to enhancing operational efficiency by enabling proactive maintenance and replacement of components before they fail. This approach minimizes the likelihood of unexpected downtime and optimizes vessel uptime, allowing for smoother and more efficient maritime operations (Makridis et al., 2020).

Eventually, predicting potential failures in the maritime domain is essential for safeguarding lives and assets as well as optimizing operational efficiency. It represents a proactive approach to risk management that is critical for the sustainable and safe operation of maritime activities.

2. Statistical-based approach

Condition-based Maintenance (CBM) is an advanced maintenance strategy that monitors the actual condition of an asset based on data-driven logic. The actual condition of the asset is continuously monitored by on-line detection of significant working parameters. The aim of CBM system is supports maintenance personnel by providing indications of performance decay in certain indicators that could result in imminent failure.

Generally, the working principles is based on the comparison with average and base-line reference values in order to indicate that the equipment is deteriorating prematurely, thus increasing the probability of failure, or, conversely, that the equipment still has a good level of performance that may allow the maintenance personnel to assess whether to postpone a maintenance activity (Hart, 2011).

In addition to online monitoring, a predictive maintenance approach leverages historical data of equipment health indices to anticipate the need for preventive actions, enabling effective planning and optimal resource management in the medium and long term. Indeed, this makes it possible to anticipate when it will be necessary to intervene with preventive actions, allowing more effective planning and optimal management of resources (Tan et al., 2012). The analysis implements a similar approach to the Stochastic Process Control or SPC method used for the control and prediction of complex industrial processes in steady state (Hjartarson & Otal, 2006).

The analysis is based on periods of stationarity in the field data, discarding transient periods. In particular, the stationary flag is validated by means of stationary concepts such as the evaluation of kurtosis, skewness, and crest factor of the gathered sample data. If the evaluated statistical values are included within a certain threshold the sample is considered stationary and it is used for the condition-based monitoring task (Heywood & McGrail, 2015).

The approach is based on baseline maintenance that involves comparing the current performance of a piece of equipment to a known baseline performance. The baseline is established by measuring the performance of the equipment when it is in good condition and using this as a reference point for future performance analysis.

The goal of maintenance analysis based on baseline is to identify changes in equipment performance that may be indicative of potential failures or maintenance needs. By monitoring the performance of equipment over time and comparing it to the baseline, maintenance teams can identify deviations from normal performance and act before equipment failure occurs.

The system accesses the baselines of the various diagnostic parameters, the baseline of each diagnostic parameter "DP" ("Diagnostic Parameter") is defined in terms of an expected value "EV" ("Expected Value") and an expected range "ER" ("Expected Range", the standard deviation). Both values are expressed as a function of control parameter: primary parameter "PP" ("Primary Parameter").

Each DP diagnostic parameter is then associated with a dimensionless diagnostic index (DI), defined as:

$$DI = \frac{|AV - EV|}{ER} \tag{1}$$

where "AV" ("Actual Value") indicates the current value of the diagnostic parameter, understood as the average value over the sampling period T adopted for the diagnostic analysis.

The diagnostic index DI is therefore always positive and has a value of 0 when the current value of the diagnostic parameter coincides exactly with the expected value, while it takes on values greater than 1 when the current value of the parameter deviates from the expected value by more than the expected range of variation of the parameter itself.

Thus, values close to zero are interpreted as indicating a normal machine condition while values close to or greater than 1 are interpreted as an abnormal condition.

Detecting anomaly signals is an essential part of any maintenance predictive system. An anomaly signal is an indication that the performance of a piece of equipment is deviating from its expected or normal behaviour. It is important to note that anomaly detection is not a one-time activity, but rather an ongoing process.

Once the DI is known the trend analysis based on the DI time series could be performed. Significant divergence from this baseline indicates potential issues. For instance, an upward trend in vibration levels beyond the established threshold may signal mechanical wear or imbalance. Similarly, an increase in temperature readings might suggest overheating or lubrication failures. These deviations from normal behaviour, identified through trend analysis, enable maintenance personnel to proactively address emerging problems before they escalate into critical failures, ensuring sustained operational efficiency and reliability of the equipment (Mazidi et al., 2016).

Eventually, maintenance predictive systems should be continually monitored and adjusted based on new data and changing conditions to ensure that anomaly signals are detected in a timely and effective manner.

The proposed description of the statistics-based system is the workflow of the On-Condition Monitoring System (OCMS) developed by Fincantieri NexTech, Figure 1, one of the CBM tools available for industrial purposes, to summarize, the logical flow of information processing by the system, from the acquisition of field data at the lowest level to the trend analysis at the highest level, can therefore be described using the following diagram, to be interpreted with a bottom-up approach:

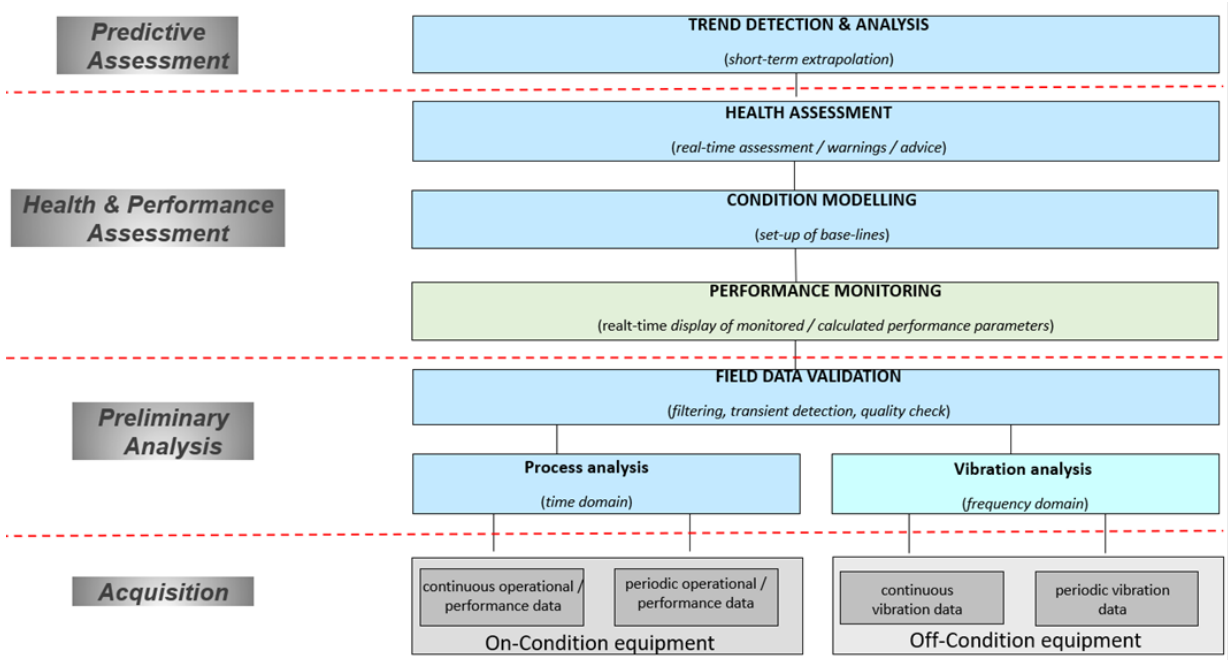

Figure 1. CBM system workflow

3. AI-based approach

In the realm of Artificial Intelligence (AI), the quest for efficient and robust anomaly detection methods remains pivotal, especially in the analysis of time series data across various industries, including finance, healthcare, and manufacturing (Pereira & Silveira, 2019). Various neural network architectures have been employed for time series analysis and anomaly detection. Convolutional Neural Networks (CNNs) excel at capturing spatial patterns, while Long Short-Term Memory (LSTM) networks are adept at modelling temporal dependencies. Autoencoders, another class of neural networks, provide a framework for unsupervised learning that can incorporate both these architectures.

This section shown the autoencoder technique, a sophisticated deep learning methodology, elucidating its role and effectiveness in identifying anomalies within time series datasets.

Autoencoders are particularly useful for anomaly detection due to their ability to learn compact representations of normal data. At their core, are a class of neural network models designed for unsupervised learning tasks. They learn to compress data (encoding) into a lower-dimensional representation and then reconstruct (decoding) the data back to its original form (Githinji & Maina, 2023). The intrinsic power of autoencoders lies in their ability to capture the most salient features of the data in the compressed representation. When applied to anomaly detection, this characteristic becomes particularly advantageous. By training exclusively on normal data, autoencoders develop a sense of 'normality' that is encapsulated in the lower-dimensional space. Anomalies, or deviations from this normality, are then detected based on the reconstruction error; a higher error indicates a data point that significantly diverges from the learned representation of normal data.

This section will further explore the intricacies of implementing autoencoders for anomaly detection in time series data, including the choice of architecture (e.g., LSTM autoencoders for handling temporal dependencies), the selection of appropriate loss functions, and the strategies for setting thresholds for anomaly detection. Practical considerations, such as handling variable-length sequences and ensuring model robustness, will also be addressed. Through this exploration, the autoencoder technique emerges not only as a powerful tool for anomaly detection but also as a testament to the versatility and adaptability of AI-based approaches in tackling complex data analysis challenges.

3.1. Data Preparation

The initial phase of proposed methodology focuses on the preparation of time series data for anomaly detection. This process encompasses fetching, preprocessing, normalizing, and structuring the data into a format suitable for ingestion by the LSTM-based autoencoder model.

3.1.1. ***Fetching and Initial Preprocessing:***

The data is fetched from a designated database, comprising primary and secondary signals associated with specific equipment. In particular, the primary signal is the one that represent more the device behaviour. In detail, these signals represent two distinct features over the same time-period, essential for constructing a comprehensive view of the equipment's operational state. The fetched dataset spans a predefined interval, delimited by start and end dates, ensuring the relevance and timeliness of the data for anomaly detection tasks. The two features that represent the apparatus, one

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representative of the load under which the systems are and the other the measure of vibration under analysis have been used.

Upon retrieval, the dataset undergoes initial preprocessing to ensure data integrity and usability. This step mitigates the influence of spurious data, enhancing the model's focus on meaningful patterns. In the train scenario it is crucial to choose a dataset representative of the good health of the apparatus under examination; this has been done because the model must learn how a good health scenario behaves to be capable, in the test phase, to recognize any anomaly by the increasing of the reconstruction error in magnitude.

Indeed, the model's ability to identify anomalies is based on deviations from the normal patterns it learned during training. This anomaly detection process does not require labelled data during the training phase but uses the learned representation of normal behaviour to flag deviations. Furthermore, the key difference between unsupervised and supervised approaches in this case lies in the use of the validation dataset. While the validation dataset is labelled, these labels are not used to train the model. Instead, the labels are only used to assess the model's performance in detecting anomalies.

Eventually, the chosen training dataset is concerning vibrational record of a bearing in the alternator apparatus of the couple “Diesel Engine – Alternator” related to the percentage of Electric Load output, for sake of clarity the data has been reported in dimensionless format.

Bearing vibration serves as a direct indicator of the mechanical health of the system, with increasing vibration often signalling developing faults or wear. However, vibration patterns can vary significantly under different operational conditions. This is where electrical load data become valuable.

The electric load data provides context for the operational state of the diesel engine-alternator couple. By correlating the bearing vibration with the electric load, the model can learn to distinguish between normal vibration changes due to varying load conditions and abnormal vibrations that may indicate a developing fault.

In Figure 2 was reported the entire dataset that has been used, the time series represent only the working day of devices, indeed, the entire dataset is composed of 95 day of recorder data.

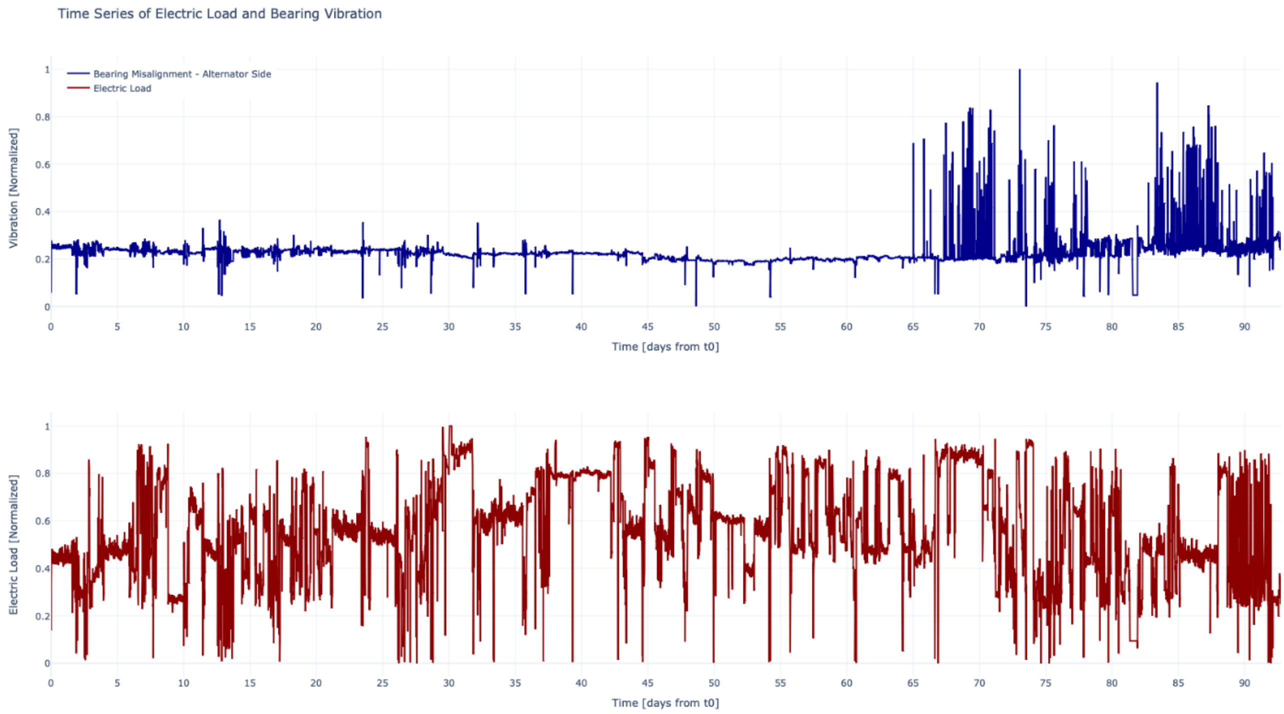

Figure 2. Bearing Vibration and Electric Load dataset.

The entire dataset was split into two parts, so that one part could be used for network training and the remainder for benchmarking. In particular, the division of the database was done knowing that the device broke down around the 95th working day the, by observing the timeseries data, the first fault symptoms started to appear around the 65th working day. The broke time was the only data available. Eventually, the time window used for the training dataset is between the beginning, the day zero, and the 46th day. The training dataset have been shown in Figure 3.

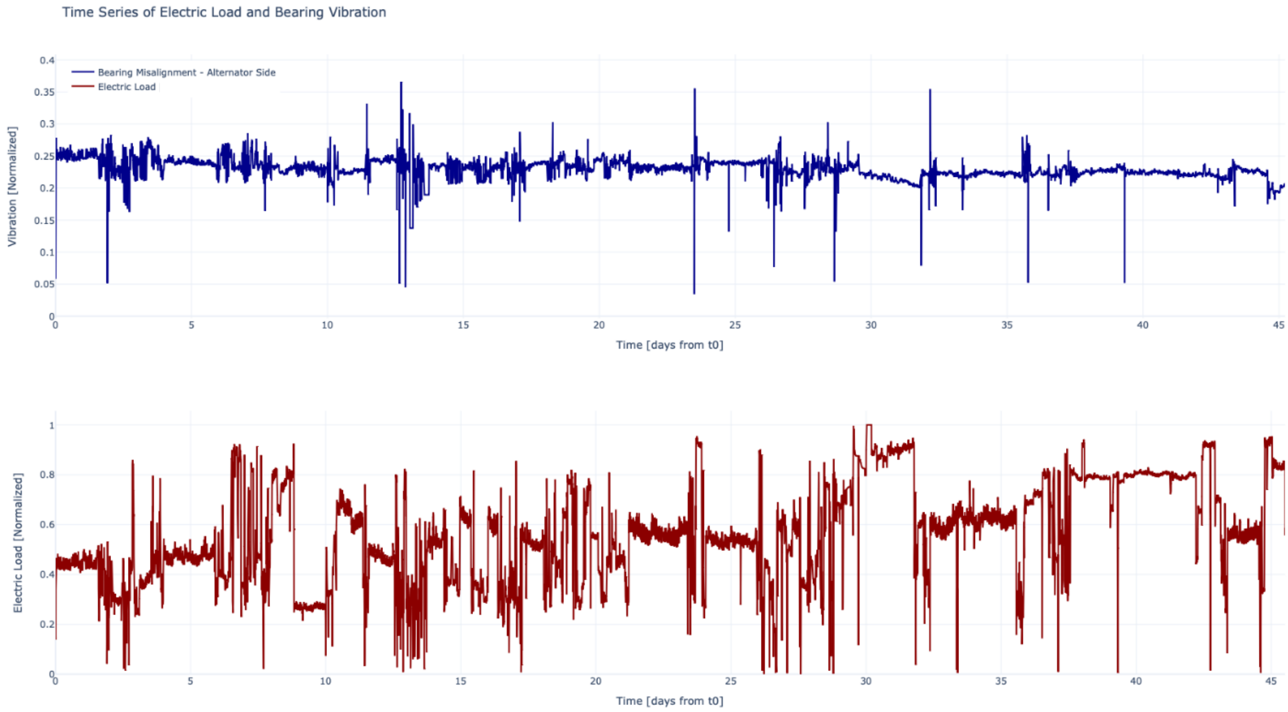

Figure 3. Bearing Vibration and Electric Load in good health status.

Those measurements represent the apparatus in a “good health” status, as no malfunctions were reported during this period. For such a reason this is have been used as data training set that will be fed to the autoencoder to learn how the bearing vibration behave in a good state of health. Instead, the benchmark is the data test represented in Figure 4 and it goes from 46th day and the day of failure, 95th day.

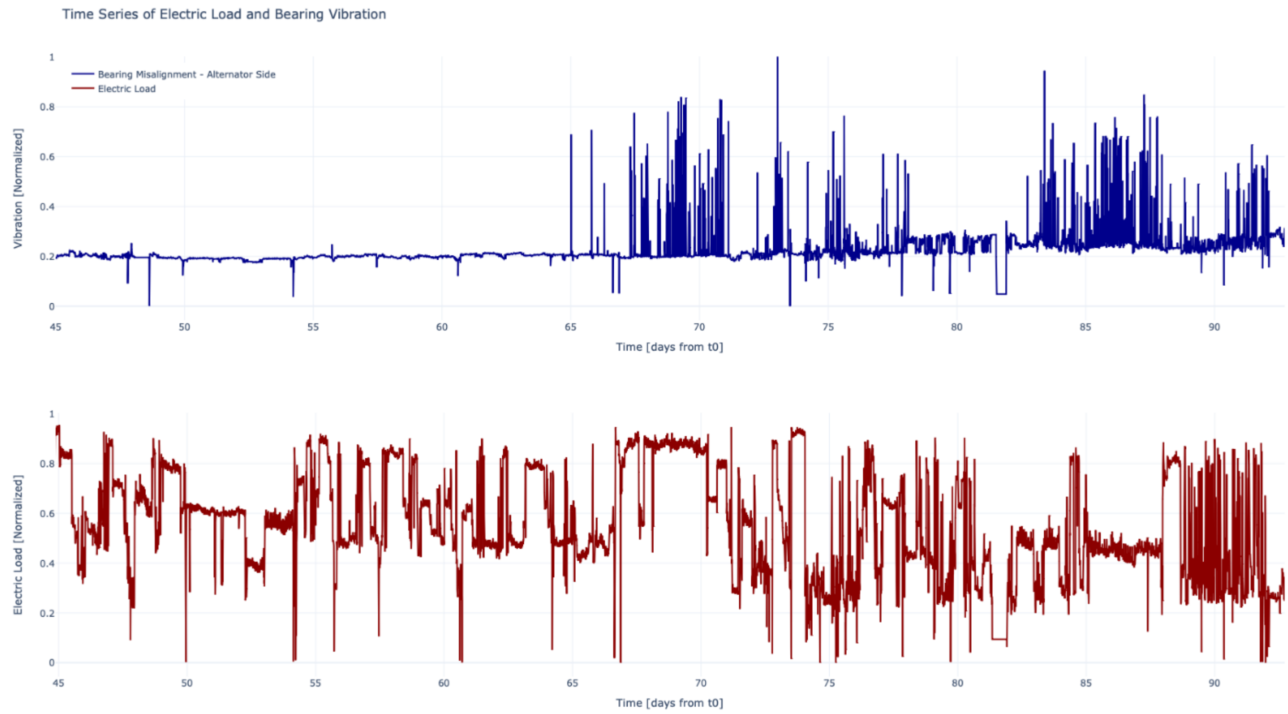

Figure 4. Bearing vibration and Electric Load anomaly.

It is notable the time representation of the anomaly as it is evolving in time; that the anomaly can be recognized, after approximately the 65th day, the bearing vibration begins to increase its peak activity (blue line).

3.1.2. Normalization

A critical component of data preparation involves scaling the features to a uniform range to transform each feature to the [0, 1] range. This normalization facilitates the model's learning by providing data in a consistent scale, crucial for the effective training of deep learning models.

3.1.3. Sequencing:

To accommodate the LSTM autoencoder's requirement for sequential data, the normalized data is structured into sequences. Each sequence, or "lookback" window, reflecting one day of data sampled at 5-minute intervals. This structuring into sequences allows the model to learn from the temporal dependencies within the data, a key aspect of its capability to detect anomalies. In this way the model must learn how the time relation subsists between all the shifted sequences.

3.2. Model Training

With the data prepared, the next phase involves training the LSTM-based autoencoder model. This training process is executed over a max of 2000 epochs with a batch size of 128, employing a validation split of 30% to monitor the model's performance on unseen data.

To enhance the model's learning efficiency and robustness, several strategies are employed:

- *ReduceLROnPlateau*: This callback reduces the learning rate when a metric has stopped improving, enabling the model to fine-tune its weights more delicately as it approaches optimal performance.
- *ModelCheckpoint:* Ensures the preservation of the model that achieves the lowest validation loss, safeguarding the most effective version of the model for future anomaly detection tasks.
- *Early Stopping:* A custom callback checks for a stop condition after each epoch, allowing for dynamic termination of training based on specific criteria, ensuring resource efficiency, and preventing overfitting.

For reference, and to show the quality of the model, in Figure 5 the trend of the loss and validation loss represented as epochs increases has been shown.

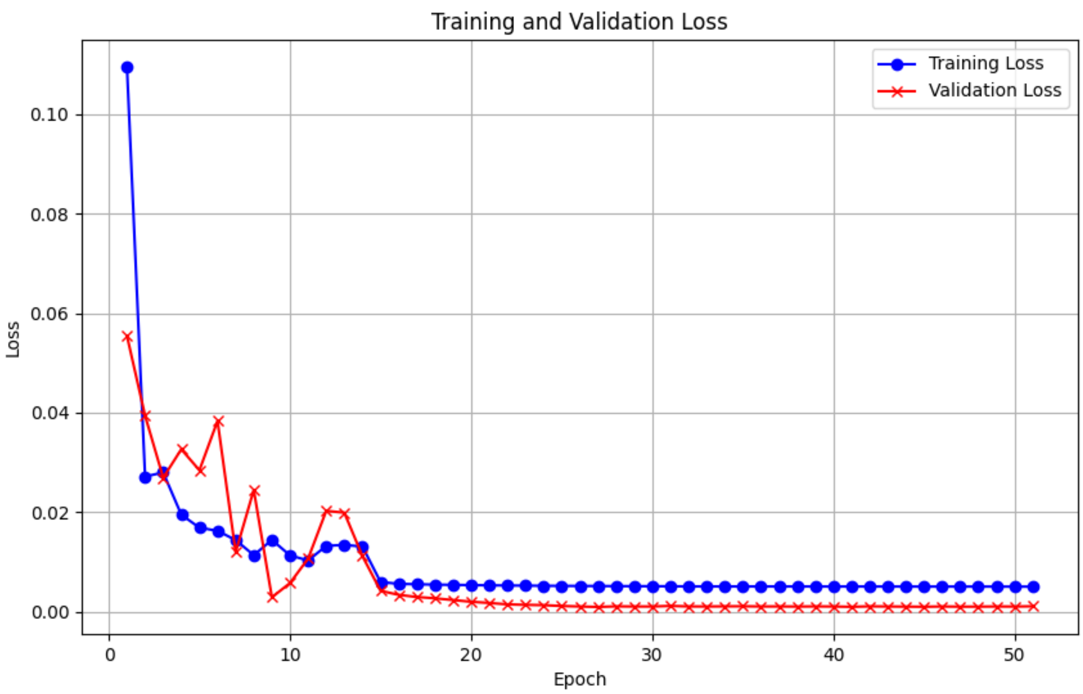

Figure 5. Train Loss and Validation Loss

It is possible to see, both training and validation loss decrease rapidly in the initial epochs, indicating that the model is learning effectively from the data. Moreover, the training loss (blue line with circle marker) continues to decrease steadily, showing the model's improving ability to reconstruct the training data. Indeed, the validation loss (red line with crossed marker) also decreases but starts to plateau earlier than the training loss. This is typical in deep learning models and suggests that the model is approaching its optimal performance on unseen data. The best performance, as indicated by the lowest validation loss, is achieved around the 30th epoch. This early convergence demonstrates the efficiency of our model architecture and training process. The early achievement of optimal performance (around the 30th epoch) highlights the effectiveness of training strategies, suggesting that further training may not yield significant improvements.

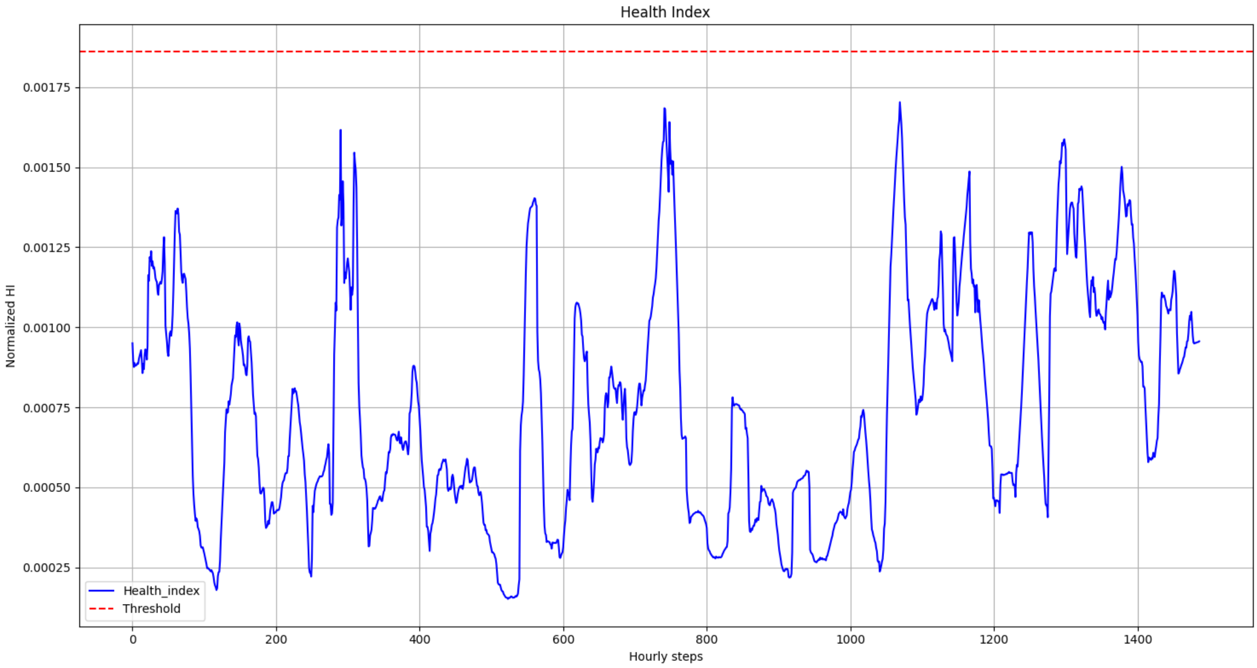

Figure 6. Health index of Trained Autoencoder

In Figure 6 the y-axis represents the Health Index, which is derived from the reconstruction error of the autoencoder. Lower values indicate better reconstruction, implying "healthier" or more normal behaviour of the system. While, the x-axis represents the time sequence of the training data, allowing us to visualize how the Health Index varies over time for known normal operating conditions. The red dashed line represents the anomaly threshold, set at the 99th percentile of the reconstruction errors observed in the training data. This threshold is crucial for distinguishing between normal operation and potential anomalies in future data. There are a few instances where the Health Index spikes above the general trend but remains below the threshold, these could represent natural variations in the system's behaviour that are still within normal operating parameters.

3.3. Anomaly Threshold Determination

The determination of an anomaly threshold is pivotal in distinguishing between normal and anomalous sequences. Following model training, the reconstruction error for each sequence is calculated by comparing the predicted output against the original input. This error reflects the model's ability to reconstruct the input data, with higher errors indicative of potential anomalies.

The threshold for classifying a sequence as anomalous is set at the 99th percentile of the reconstruction errors observed across the training dataset.

This threshold is chosen to identify the most significant deviations from the norm, capturing only the most pronounced anomalies. By focusing on these extreme discrepancies, the model effectively flags sequences that markedly diverge from the learned patterns of normal operational data, thus identifying potential issues or anomalies within the equipment's functioning.

4. Results; Identify an anomaly and the RUL line trend.

The proposed approach considers real-world application constraints. Indeed, for industrial applications, obtaining end-of-life (EOL) data is often challenging. This difficulty arises primarily because the complexity of an apparatus can varies significantly within the variables under observation. Consequently, the variables that must be monitored encompass a set of machinery that manufacturers typically do not provide with detailed EOL dynamic curves. Secondly, the aim is to develop a holistic approach applicable to every system without requiring a priori knowledge of threshold locations.

Moreover, as the system is used over time and more data are collected, thresholds can be adjusted based on empirical evidence.

Following these observations, Remaining Useful Life (RUL) analysis was initiated through examination of trend patterns in the data. The objective was to identify any trends or dynamic changes in the sequence under analysis, determining whether the system was entering a degradation regime or experiencing sudden, severe degradation. This analysis was conducted using linear interpolation of the Health Index (HI) over the last n days.

The purpose was to ascertain if anomalies could be detected before the HI effectively surpassed the established threshold, as shown in Figure 7. In particular, the figure shows the trend analysis assuming that the analysis was conducted the day before the first appearance of anomaly in the HI, i.e., the 64th day.

The RUL was interpolated for the last 11, 15, 19, and 21 days, and the intersection point of the trend line with the threshold was determined. Notably, each plot shows within the white box the number of days to reach the threshold value. Indeed, the mean RUL was assessed using these four RUL estimates. In this case, the estimated time to reach the danger zone is 212 days; this can be seen as a general indicator of the HI trend.

The first symptom of anomaly occurred on the 65th day when the magnitude of vibration became visible (Figure 4). Examining the four graphs individually as the observation period window varies, it becomes evident that shorter observation periods yield more sensitive but unstable forecasts. Conversely, longer windows produce more stable forecasts but are unable to capture sudden threshold exceedances. For this reason, as a first approximation, an average assessment of threshold exceedances was chosen.

On the 65th day, the system exhibited anomalous vibration magnitude, and the model detected this anomalous behaviour as the HI exceeded the HI threshold, as shown in Figure 8. A point of the HI crossed above the threshold, showing a value of 0.0041. Consequently, RUL interpolation showed a consistent drop in the time to intercept the threshold guard to 7.5 days, indicating that the system might be in a state of degrading performance.

Moving forward in time, the behaviour of the HI validates the advanced degradation state of the system. Figure 9 shows the prediction made at day 72, where the magnitude of the HI jumps to 0.07, with a clear upward trend indicating pronounced degradation in the apparatus's performance. Indeed, the prediction for the 11-day observation window is assessed as "already happened" for the intersection value between the HI threshold and the trend curve.

To obtain definitive confirmation of the apparatus's new degradation state, HI prediction was carried out until the end of the data, where the apparatus reached definitive failure on the 92nd day. This is represented in Figure 10, showing that the system remains above the threshold throughout the period until the apparatus's failure. It is worth emphasizing that once the threshold has been reached, the interpolation of the last days of the RUL loses its informative significance, as shown for the 11-day observation window.

In conclusion, this analysis demonstrates the effectiveness of the proposed approach in detecting and tracking system degradation over time. The method successfully identified the onset of anomalous behaviour and provided valuable insights into the progression of the system's health status, offering potential for early intervention and maintenance planning in industrial applications.

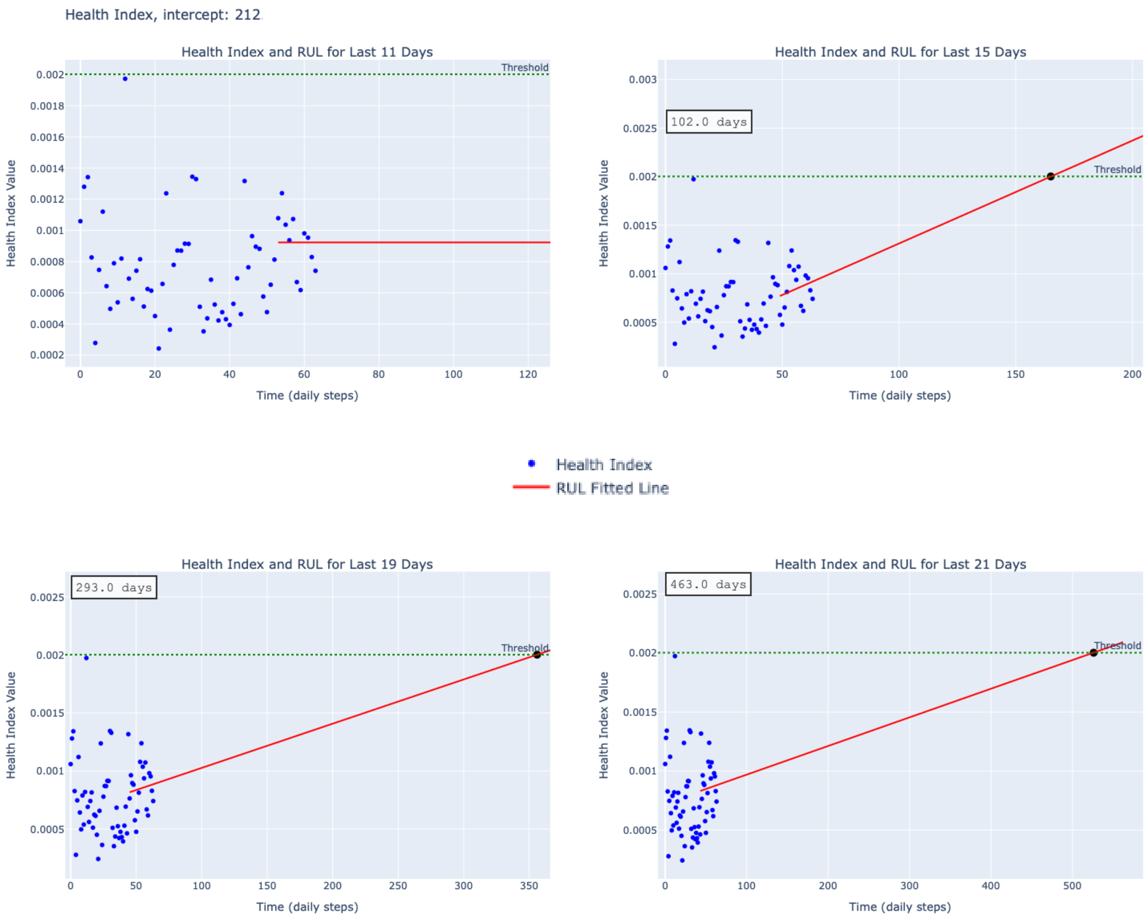

Figure 7 - RUL fitting for last 11, 15 19, 21 days at 64th day.

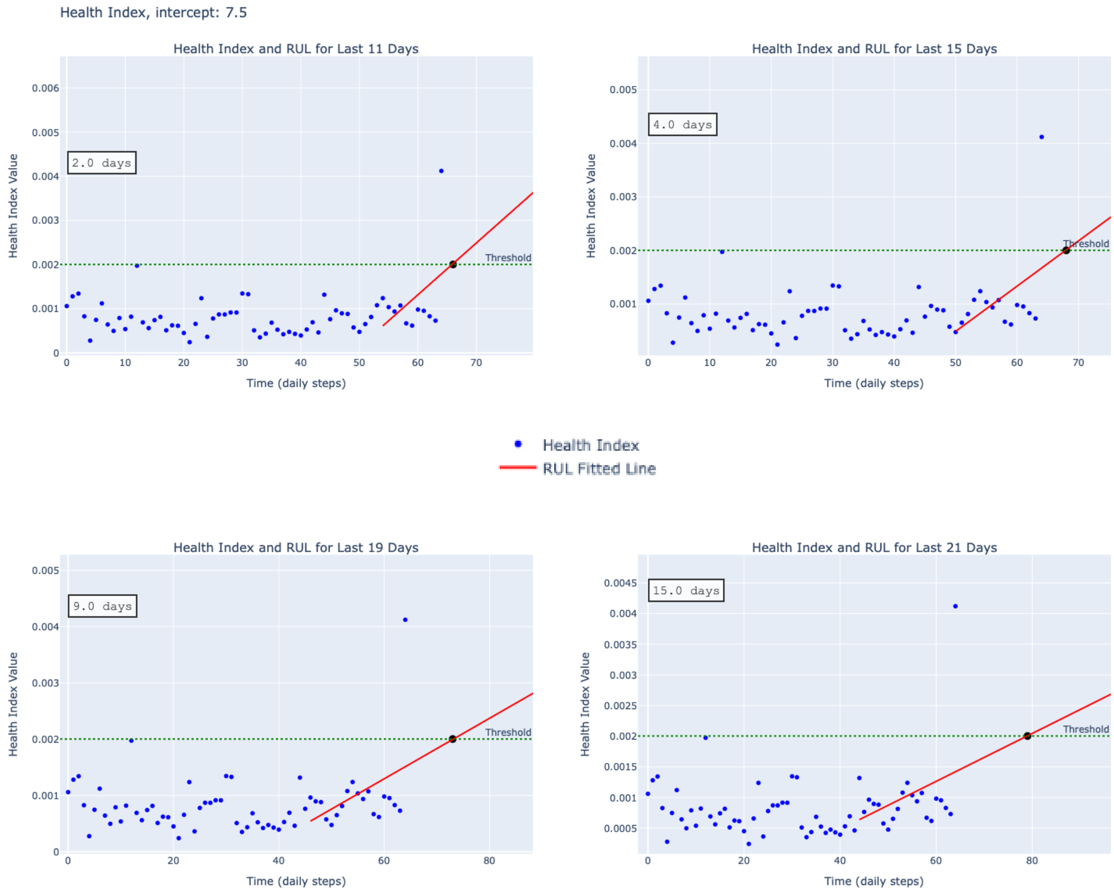

Figure 8 - RUL fitting for last 11, 15, 19, 21 days at 65th day

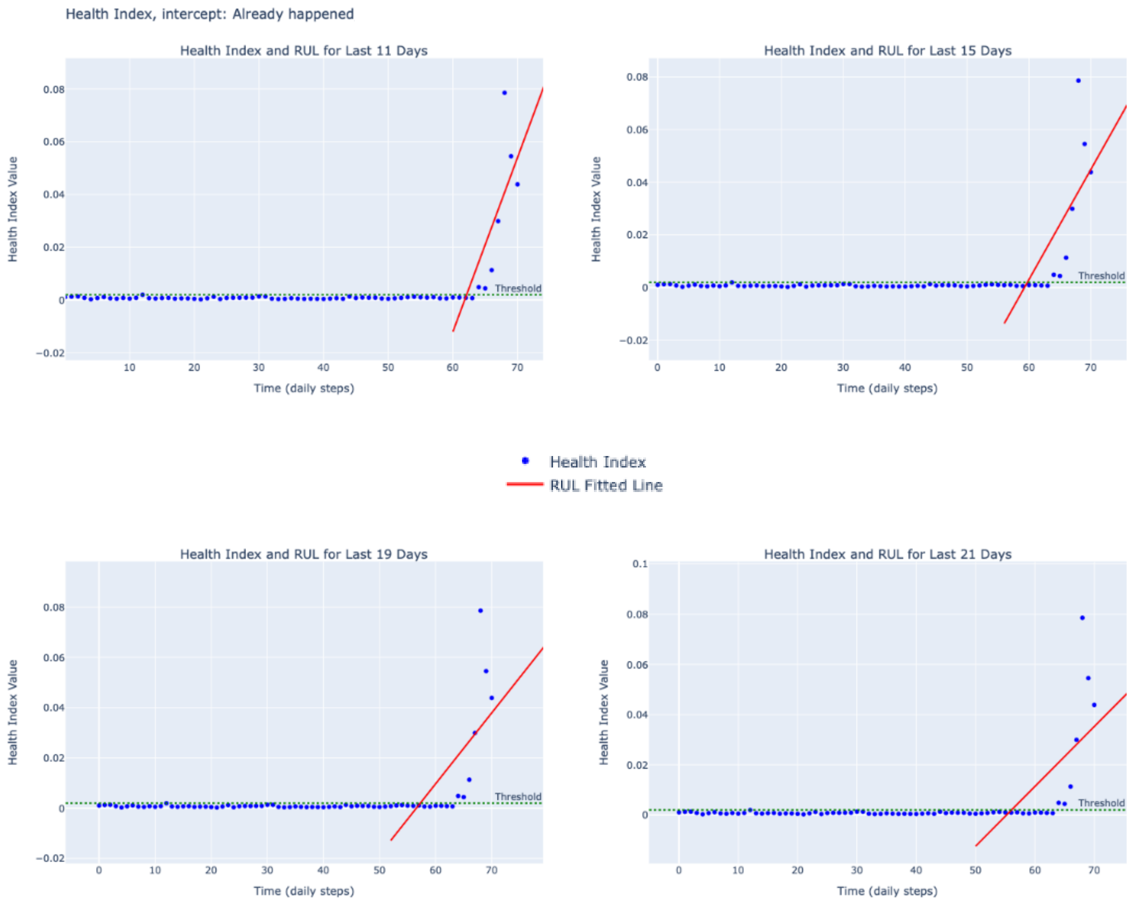

Figure 9 - RUL fitting for last 11, 15, 19, 21 days at 72nd day.

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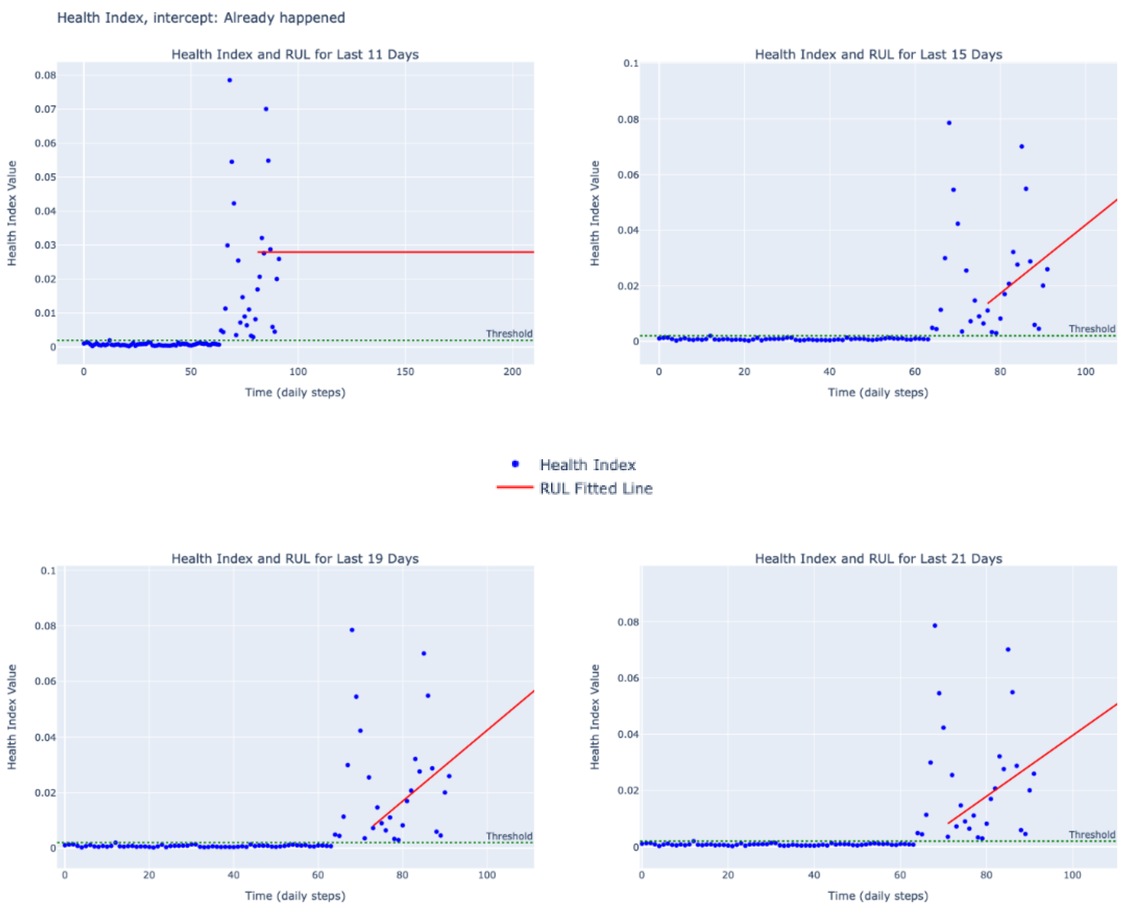

Figure 10 - RUL fitting for last 11, 15, 19, 21 days at near-end dataset.

5. Conclusions & developments

The research successfully implemented an LSTM-based autoencoder for anomaly detection in marine equipment sensor data. The model demonstrated the ability to identify developing faults in the bearing, as evidenced by changes in vibration patterns. The approach showed promise in handling data from different engine load profiles, suggesting potential adaptability to various operational conditions.

While not extensively discussed in this paper, preliminary observations suggest that the proposed method may offer improved fault tracking capabilities compared to traditional statistical approaches. However, a comprehensive comparative study will be carried out to quantify these potential advantages.

The results suggest that the proposed methodology has potential for enhancing predictive maintenance practices in maritime applications. By leveraging unsupervised learning techniques, this approach may be particularly valuable in scenarios where labelled failure data is scarce or unavailable.

However, it is important to note the limitations of this study. Detailed comparisons with conventional methods were not performed within the scope of this paper. Future work should focus on conducting comprehensive comparative studies with traditional statistical methods and other machine learning approaches to quantify potential improvements in predictive accuracy. Additionally, expanding the range of fault types and operational conditions tested would further validate the method's generalizability. Investigating the integration of this approach with existing maintenance systems in real-world maritime operations is also an important area for future research.

In conclusion, while this study demonstrates the feasibility and potential of the proposed unsupervised learning approach for marine equipment predictive maintenance, further research is needed to fully establish its comparative advantages and practical implementation challenges in real-world scenarios.

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