FAULT DETECTION IN TUGBOAT MARINE DIESEL ENGINES THROUGH THE APPLICATION OF MACHINE LEARNING – A REVIEW

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Abstract — **With the advent of Industry 4.0 and equipment connected to the Internet of Things (IoT), predictive maintenance—in conjunction with diagnostic systems and intelligent fault detection based on data and Artificial Intelligence (AI)—has been a subject of study and research for several years. Utilizing these tools with data originating directly from monitoring sensors aims to guarantee equipment availability and identify signs of failure even before an experienced technician can detect them. Currently, maintenance planning and control systems may not provide the precision expected for effective action. This occurs because information input is performed manually by the operator and may be done incorrectly, whether due to the non-performance of the proposed service or the language presented in the manual being misunderstood by the operator, hindering the evaluation by the maintenance planner and the diagnosis of an imminent failure. By opting for data-based predictive maintenance, the goal is to improve assertiveness, reduce costs from unnecessary parts replacements in preventive maintenance, and reduce the probability of breakdowns. In the maritime field, an increase in the search for these solutions is observed in vessels due to the increased data collection capacity of equipment with new onboard technologies. During vessel operations, the challenge of applying intelligent monitoring systems stands out primarily due to the complexity of the equipment and non-constant operating profiles, unlike industries with static assets. Consequently, maritime companies currently rely on preventive maintenance scheduled by the manufacturer and corrective maintenance, which can be operationally and financially costly. The application of fault and anomaly detection methods in marine diesel propulsion engines is essential to complement preventive methods, ensure safety, and maintain vessel operation. These engines are usually large-scale, making their maintenance complex and non-trivial, requiring hours or days of downtime to perform the work. This work presents a preliminary literature review concerning fault detection methodologies in marine engines, with the goal to apply in tugboat operations, serving as an initial component of a research project shared for academic discourse rather than as a formal peer-reviewed publication.**

Keywords — *Machine Learning, Marine Engine, Tugboat, Predictive Maintenance*

I. INTRODUCTION

To meet their objectives of towing and mooring large ships, modern port tugboats are equipped with at least two large-scale diesel engines. These engines function across various operational ranges, from low loads during transit to maximum power when performing pulling or pushing manoeuvers. For the owners of these vessels, the shipowners, ensuring that this equipment does not fail during an operation is essential.

In this way, operation and maintenance teams are dedicated to ensuring that the engines maintain consistent performance, in addition to preventing or identifying failures in advance. A failure that could shut down the diesel engines during operation can cause not only financial losses but also serious accidents due to the loss of static bollard pull and loss of steering. [1] evaluated contributing factors for types of accidents involving port tugboats and demonstrated in his research that failure of the hull/propulsion system represents 33.8% of these.

To avoid serious failures, shipowners adopt preventive maintenance methodologies based on manufacturer calendars or operating time. However, because they do not consider the actual condition of the equipment, these practices can lead to the unnecessary replacement of parts or the neglect of problems not foreseen in maintenance [2]. Before a failure occurs, there are generally signs of malfunction that may go unnoticed by the crew [3], highlighting that a data-driven maintenance approach not only tends to reduce maintenance costs but also ensures that by maintaining constant monitoring of the main engines, there is the possibility of reducing harmful gas emissions.

The challenge regarding the accuracy of maintenance planning systems often lies in human factors, given that equipment condition information is manually entered into these systems. Incorrect information entry may not reflect the actual condition of the machinery, leading to poor planning regarding the correct timing and the necessary parts for maintenance. The application of data-driven predictive maintenance provides an opportunity to reduce failure risks through the constant capture of equipment information. This subject has been the focus of recent research and development in the maritime sector, driven by advancements in data analysis capabilities, and is a topic of ongoing monitoring by classification societies [4].

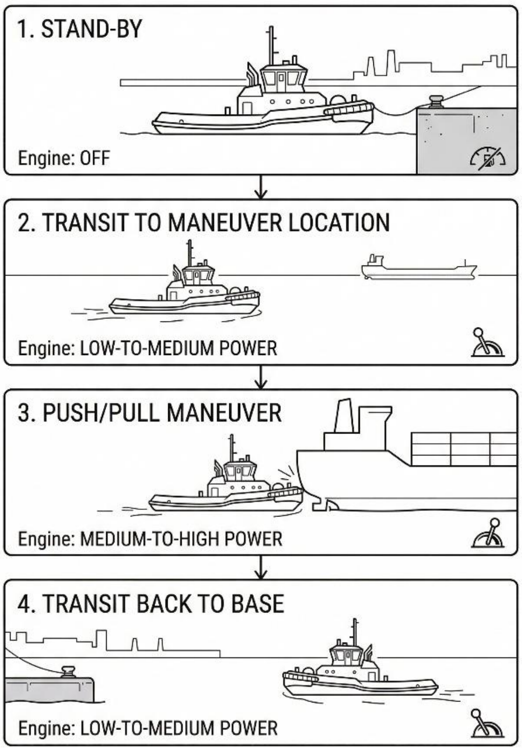
There are various nomenclatures and applications for using data in predictive maintenance decision-making, such as Prognostics and Health Management (PHM), Fault Detection and Diagnosis (FDD), and Intelligent Fault Diagnosis (IFD), among others. Most of these focus on predictive maintenance by applying data analysis and machine learning for continuous monitoring, identifying anomalies in each subsystem even before a human specialist, which enables maintenance to be performed only when necessary [2].

A. TUGBOAT OPERATIONS

Port tugboats are primarily designed with a focus on static bollard pull, which is the traction exerted by the tug at maximum power and zero speed. Unlike other merchant vessels, port tugs operate across various rotation and power ranges within short periods according to operational demands. In a basic operational scenario, a tugboat follows at least 4 of these cycles as illustrated in Figure 1.

Such variations in operational patterns can hinder the application of fault detection and diagnosis methods reported in the existing literature. Consequently, it is necessary to study the need for segmenting these operational moments to identify anomalous engine trends correctly.

Figure 1 – Tugboat Operational States



Source: Author

B. MAINTENANCE CATEGORIES

The nomenclature for different types of maintenance is typically applied based on the reasons driving the intervention in the equipment. According to [5], maintenance can be divided into two main categories: 1) corrective maintenance; and 2) preventive maintenance. The latter is further subdivided into condition-based maintenance and predetermined maintenance. In their study, the authors describe other maintenance methods that can be applied as subcategories of these main classifications.

According to [2] another categorization possibility can be attributed, which includes predictive maintenance as a primary branch alongside those previously mentioned. This approach relies on continuous monitoring and machinery sensing data, allowing interventions to be performed only when necessary. Each maintenance type offers specific benefits; however, an effective maintenance strategy should improve equipment conditions, minimize failures, and reduce maintenance costs while simultaneously maximizing machinery operation.

II. LITERATURE REVIEW

In this section, a literature review will be conducted with a focus on the application of machine learning algorithms for equipment monitoring and fault detection, emphasizing applications within maritime contexts.

A. EQUIPMENT FAULT DETECTION

[6] Provide a comprehensive review of machine learning applications for fault detection in general. In their study, the authors highlight that intelligent fault detection involves applying machine learning algorithms to continuous monitoring data, representing a promising approach for this purpose. The work outlines an evolutionary roadmap for these applications, initially addressing past uses based on traditional machine learning methods. It notes that with these methods, diagnostic models began to identify and establish relationships between collected attributes and the current state of the equipment, motivating the introduction of Artificial Intelligence for this task. Continuing the analysis of the current state of the art, driven by the use of deep learning, the authors mention that as data volume increases, traditional methods can no longer meet requirements due to low generalization, which reduces model accuracy. They suggest deep learning as an approach to solve this problem. Finally, the article explores future perspectives, highlighting the potential of transfer learning techniques to further enhance fault detection effectiveness. They explain that knowledge can be transferred from a source, where tests and fault detections were performed, to a target application in operational scenarios. An example provided is the possibility of simulating bearing failure scenarios in a laboratory to train models and then utilizing these results in industrial applications.

[7] Presents data-driven monitoring as the application of statistical methods and machine learning to detect and diagnose faults in industrial processes. There are two main approaches: modeling for all types of faults and modeling for the normal case, with the latter being more common for identifying deviations from the operational pattern. The study emphasizes industrial applications using Principal Component Analysis (PCA) and Partial Least Squares (PLS).

B. CLASSIFICATION SOCIETIES PERSPECTIVES

There is a notable research opportunity for fault detection methods within the maritime sector, as classification societies are now publishing recommendations for implementing prognostic health management systems.

Classification societies are organizations responsible for the certification, inspection, and safety assurance of merchant vessels throughout their entire life cycle. These entities develop strict rules and criteria to meet national and international standards set by maritime authorities, aiming for operational safety and the safeguarding of human life [8]. By classifying a vessel, the entity ensures that it has adhered to the conditions established in its rules and regulations.

According to [4], members of classification societies evaluate that traditional preventive maintenance methods—

which involve fixed calendars for part replacement—are an approach that typically results in excessive downtime and unnecessary costs. With the implementation of technologies for data-driven monitoring and maintenance, the authors mention that periodic class surveys will not be replaced but will instead become more efficient and targeted. The authors assess data-driven maintenance, or prognostic health monitoring, which focuses on data collection and monitoring the health of the equipment. This is an approach that utilizes real-time data analysis to predict potential failures or the remaining operating time to optimize maintenance activities.

Although classification societies are not directly involved in the development of these applications, they play a fundamental role in regulating and ensuring the correct use of these systems. The authors define the main nomenclatures found in the literature regarding monitoring and fault detection applications, as shown in Table 1. Furthermore, it is noted that across various implementation possibilities, the development of Prognostics and Health Management (PHM) solutions is based on three primary steps: 1) Data acquisition and processing; 2) Fault diagnosis and prognosis; 3) Maintenance decision-making.

Table 1 - Definitions

Abbreviation	Meaning	Description
CM	Condition Monitoring	The process of monitoring equipment conditions to capture early stages of wear and tear.
CBM	Condition Based Maintenance	A maintenance strategy derived from data collected through CM to determine the appropriate timing for an intervention.
RCM	Reliability Centered Maintenance	A process used to determine necessary actions to keep equipment operational based on operational requirements and history.
PHM	Prognostics and Health Management	An advanced approach that combines CM, CBM, and RCM using real-time data analysis and potential fault detection.

Source: adapted from [4]

[4] point out that the application of fault detection methods is challenging for stakeholders, and that most remain only with CM, while few advance to CBM. The authors add that in the maritime segment, despite vessels being equipped with various sensors for data collection, the use of data analysis and the application of machine learning for fault prediction is not widespread. The primary concerns of those involved are data privacy and security, as well as the need for technical knowledge to develop and use these applications. Nevertheless, there is a noticeable growth in the demand for these solutions, given the possibility of improving efficiency and reducing maintenance costs. Classification societies should focus on standards and best practice guides aimed at the effectiveness and reliability of such systems. In the study, the authors mention that classification societies are demonstrating favourable views regarding the development and application of PHM systems. These entities already have rules and guides addressed to CM and CBM, despite the limited and slow adoption of such systems in the maritime sector. The authors also cite rules published by the companies DNV and ABS, which establish regulations, structural guides, and possibilities for assigning class notation to vessels that follow them—for example, the SMART notation, assigned by ABS to vessels that adhere to its rules and guidelines. When addressing future challenges, the authors highlight the guarantee of data quality for machine learning models and note that these models require continuous quality monitoring, updates, and calibration to ensure their effectiveness.

Intending to disseminate the perspective of a classification society, Lloyd's Register published a guide of recommendations for the application of Data-Driven Condition-Based Maintenance (DCBM) [9]. This guide describes the main disadvantages of traditional maintenance methods, such as the lack of integration of available data for better understanding and assertiveness in maintenance strategies. It emphasizes that despite the increased availability and accumulation of data volumes in recent vessels, members of the maritime ecosystem lack clear knowledge on how to apply and utilize this resource to gain operational advantages. Consequently, shipowners persist with traditional methodologies that can be inefficient and costly. Furthermore, there is a lack of integration between equipment manufacturers and shipowners regarding the collection of data from their equipment.

According to the authors, several factors contribute to the characteristic inefficiency of traditional maintenance methods. First, scheduled inspections are typically based on accumulated usage time, requiring operators to perform visual investigations to assess equipment condition. Second, subjective assessments often prevail, which are heavily dependent on the individual knowledge and experience of the specific evaluator. Third, reactive maintenance involves conducting interventions only after equipment demonstrates a failure, which can potentially leave the entire system out of operation.

Furthermore, there is a limited use of sensor data; current information is usually underutilized, serving primarily as a tool for triggering alarms and rarely being integrated into a proactive maintenance strategy. Finally, records and documentation rely on manual maintenance and inspection logs that are prone to human error and do not support the in-depth data analysis required for predictive maintenance strategies.

In their study, Lloyd's Register mentions that the aviation sector has achieved a 30% reduction in maintenance costs and a 5% to 10% reduction in calendar-scheduled maintenance costs through the application of data-driven maintenance. They weigh two expected outcomes of data-driven maintenance: proactive failure prevention or the minimization of failure impacts. The authors summarize the main challenges that the development and application of DCBM can address, highlighting two topics relevant to this research project: the inadequate timing of maintenance periods and inspection activities, and the failure to precisely diagnose equipment condition. For shipowners, it is expected that the adoption of these applications will not only reduce the frequency of asset maintenance but also lower operational expenses. Finally, the authors issue a challenge to encourage stakeholders in the maritime segment to invest in digitalization and the implementation of DCBM, given these significant benefits.

C. FAULT DETECTION IN MARITIME ENGINES

Main engines are the most critical equipment on a vessel, as they serve as the primary source of power and energy for onboard operations. Marine diesel engines are large-scale and more complex than those typically found in the automotive sector [10]. Unexpected failures that cause a reduction in energy efficiency or a total service interruption can lead to economic losses and, in extreme cases, pose risks to human life [11].

In [11], the authors conducted a review of existing research on the application of Fault Detection and Diagnosis (FDD) specifically for marine diesel engines. The authors observed a structured division into causes of failures within this equipment, categorized into four main systems: Fuel injection system, Lubrication system, Cooling system, Intake and exhaust system.

Without specifically mentioning a particular nomenclature for methods or systems, [10] states in their review that researchers are turning their attention toward utilizing sensor data and machine learning to improve the detection and prediction of failures in marine diesel engines. The author separates fault diagnosis methods into three main categories: model-based, knowledge-based, and data-based, focusing their review work on the latter. In addition to the aforementioned categories, [11] addresses hybrid methods, which utilize a combination of elements from other approaches with the goal of improving the final result.

Through the reviews conducted by [11], the effectiveness of applying machine learning algorithms for fault detection in marine engines is noted. The primary advantages highlighted include increased efficiency in fault identification and the ability to evaluate a large volume of attributes and data simultaneously, a task that would be unfeasible for a person, even an experienced one. However, the literature also demonstrates challenges in these applications, mainly due to the dependence on high-quality data and the interpretability of the paths and rules used by the models. This is particularly true for deep learning models, which are often considered black boxes. This lack of model visibility remains a concern for stakeholders in the maritime segment.

Various algorithms are currently being studied for maritime applications. For instance, Support Vector Machines (SVM) have proven to be a widely researched method for these issues, particularly in diesel engine subsystems and in conjunction with Principal Component Analysis (PCA) and wavelet analysis to detect cylinder head faults. Ensemble methods are also prominent as they combine results from multiple techniques; decision trees, for example, demonstrate high accuracy in fault detection. Furthermore, Artificial Neural Networks and deep learning methods—which can be integrated with other approaches—frequently appear in research focused on fault detection systems and engine performance monitoring.

Table 2 summarizes some additional papers that evaluate the application of methods for FDD in ship machinery.

Table 2 – FDD Research

Author	Methods	Ship type/Equipment
[12]	Review	Details of recent applications in maritime systems
[13]	Random Forest and Artificial Neural Networks	Simulated diesel engine / lubricant circuit
[14]	Digital Twin: Random Forests + Optimization + Virtual Engine	8-cylinder diesel engine on a test bench
[15]	Isolation Forest + SHAP	Diesel engine in a General Cargo Ship
[5]	Operating limits analysis	Main engine of a seismic research vessel

Source: Author

III. CONCLUSION

The transition toward Industry 4.0 and the Internet of Things (IoT) has fundamentally redefined the landscape of maritime maintenance. As established throughout this literature review, traditional strategies—primarily preventive maintenance based on fixed manufacturer calendars—often fail to account for the actual condition of equipment, leading to unnecessary downtime, inflated costs, and unforeseen catastrophic failures.

In the specific context of port tugboats, these inefficiencies are exacerbated by the extreme operational complexity of marine diesel engines and the non-constant load profiles inherent to pulling and pushing maneuvers. Research underscores that human error in manual data entry remains a significant barrier to accurate diagnosis. However, the integration of Machine Learning and Deep Learning offers a transformative solution, enabling the simultaneous analysis of vast sensor data volumes to identify early signs of wear that escape human observation.

Classification societies, including ABS, DNV, and Lloyd's Register, are increasingly recognizing this potential, issuing guidelines for PHM and DCBM to ensure these systems meet rigorous safety and reliability standards. While challenges such as the black-box nature of deep learning and data quality remain, the move toward a data-oriented paradigm is essential for maximizing operational availability and environmental efficiency.

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