Control and Robotics Express Communications
https://www.sciltp.com/journals/crec

Article

Fault Prediction and Condition-Based Maintenance of Marine Engines

Francesco Maione [1], Paolo Lino [1], Giuseppe Giannino [2], Erlend M. Coates [3], Ottar L. Osen [3] and Guido Maione [1,*]

[1] Department of Electrical and Information Engineering, Polytechnic University of Bari, 70125 Bari, Italy
[2] Center of Innovation and Development, Isotta Fraschini Motori S.p.A., 70132 Bari, Italy
[3] Department of ICT and Natural Sciences, Norwegian University of Science and Technology, 6025 Ålesund, Norway
* Correspondence: guido.maione@poliba.it; Tel.: +39-080-5963247

How To Cite: Maione, F.; Lino, P.; Giannino, G.; et al. Fault Prediction and Condition-Based Maintenance of Marine Engines. *Control and Robotics Express Communications* **2026**, *1*(1), 4.

Received: 2 April 2026
Revised: 4 May 2026
Accepted: 27 May 2026
Published: 15 June 2026

Abstract: The development and implementation of machine learning and deep learning algorithms has opened up new possibilities in industry. Maintenance of industrial assets has received wide interest from scientists and practitioners. Condition-based maintenance (CBM) has proven to be necessary to reduce downtime and the cost of repairs and inspections, and to predict and prevent faults. In the maritime industry, marine engines are complex systems that must work in a rough environment; therefore, implementing safe, reliable, and efficient maintenance strategies is challenging. In this context, artificial intelligence (AI) algorithms have shown high reliability and versatility with respect to traditional model-based and knowledge-based techniques. In this work, we propose an unified framework explaining the implementation of suitable AI algorithms to predict the main faults affecting the performance of a marine engine. By an accurate analysis, aging and catastrophic faults are the most common ones. Then, we describe strategies to detect these two types of faults. We also describe the requirements that a decision support system should satisfy to integrate the algorithms for applying an innovative CBM strategy into real-life scenarios. Finally, we present the challenges and provide some suggestions for future research. In summary, the main finding of this work is the framework integrating AI-based efficient strategies for predicting aging and catastrophic faults with significant advance. In detail, prediction of catastrophic faults gains nearly 30 seconds with respect to a classical prediction method. These findings enable us to effectively implement CBM of marine engines considered in this research.

Keywords: condition-based maintenance; fault; predictive algorithm; artificial intelligence; marine Diesel engine; decision support system

1. Introduction

The development and implementation of models, control systems, and optimization algorithms based on Artificial Intelligence (AI) are forcing a paradigm shift in several industries, such as those producing engines for ships and marine vehicles. The Shipping 4.0 concept has been coined to represent the digitalization and automation of the maritime and logistics sector [1]. The goal is to reduce production and maintenance costs, improve the safety of operations and people, track vehicles and goods in real time while securing them, save energy and optimize use of resources, and reduce the environmental impact of naval operations. In fact, maritime transport is very important for the world and EU economy: 75% of EU international trade takes place by sea and Europe has the highest number of passenger transports by water, which are increasing after the COVID-19 pandemic. The integration of intelligence allows cooperation and symbiosis between humans and machines.

1.1. Condition-Based Maintenance Paradigm

In the described scenario, autonomous shipping, ship digitalization, intelligent energy management, and cyber-security are becoming increasingly important. Research also highlights a change of paradigm in maintenance procedures, especially those related to the core of every ship, i.e. its propulsion plant. By the European regulation EN 13306:2018, maintenance is the combination of all technical, administrative, and managerial actions during the life cycle of an item to retain it in, or restore it to, a state in which it can perform the required function. Lack of maintenance can have a significant environmental impact because a malfunctioning machine emits more harmful substances than a machine that is functioning properly [2]. Moreover, downtime could have serious cost consequences, and faults could cause safety concerns for crew and passengers [3,4].

Until today, maintenance has generally been reactive in nature, i.e. based on repair or replacement of failed components, or time-based, i.e. based on statistical observations and inspection audits planned at fixed time intervals, similar to scheduling problems. The preventive maintenance [5–7] overcomes the limits of reactive maintenance, which only intervenes after the fault has occurred [5–7]. However, the risk of unexpected downtime is lower than with a reactive approach, but it is still not zero; moreover, the unnecessary audits and use of parts when the machine is still healthy increase the cost of maintenance and can introduce faults, for instance due to incomplete or incorrect reassembly. Since that, predictive maintenance by machine learning (ML) and deep learning (DL) algorithms has clear advantages like reducing the number of unplanned and unnecessary downtime and increasing the safety of transported goods and people. The classification of maintenance approaches is shown in Figure 1.

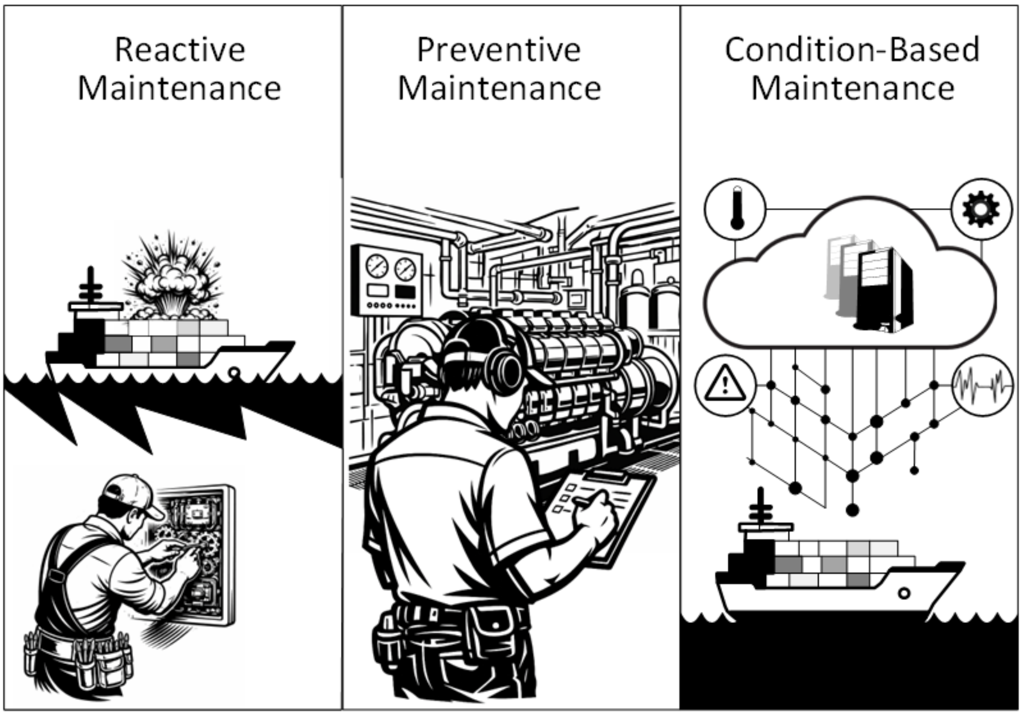

Figure 1. Approaches to maintenance.

To begin with, we clarify the main definitions. The literature records the terms condition-based maintenance (CBM), predictive maintenance (PdM), and prognostics and health management (PHM) that can indicate the same or different strategies to solve the same problem. In fact, PdM [8–10] and PHM [5,6,11] focus on predicting the trend of significant variables such as the remaining-useful-life (RUL) of the monitored asset. The RUL is the time interval between the current operating condition and the occurrence of the fault. On the contrary, CBM emphasizes that the continuous monitoring of the status of equipment is the key to determine maintenance operations [12]. Both PHM and CBM use sensor data to evaluate the RUL. In this work, we consider CBM, PdM, and PHM as synonyms. In fact, the RUL prediction is impossible without monitoring the engine in a continuous way.

On the other hand, as highlighted by [13,14], CBM is hindered by its upfront implementation cost due to the additional hardware and software required (advanced sensors, wiring, data acquisition systems and computers, tailored numerical codes). Moreover, marine engines require storing and processing a tremendous amount of data and CBM is possible only through advanced technologies and qualified technicians [14,15]. However, the minimization of both unexpected faults and unnecessary idle time allows us to save money, reduce use of spare parts and labour costs, increase the life of the components and the safety of the ship, passengers, and transported goods. These benefits increase the profit of the shipping company and return the initial investment.

The CBM can be applied through online or offline monitoring. The second method consists in acquiring information when the asset is not working, e.g. by vibration analysis [16], oil samples [17], and wave spectrum analysis [18]. However, most of the interest is in online methods, since they protect the ship's engines for the entire running time. Today, CBM is often hardcoded rules with alarm limits (say overall vibration as in rotary steerable systems or specific frequencies above a threshold). Then, AI can support online CBM by the following approaches:

- Knowledge-based: algorithms are designed to mimic the experts' reasoning, like in Bayesian Networks [17]. The drawback is that, for new prototype engines or hydrogen fuel cell engines [19], the availability of experts is not a given.
- Model-based: an accurate mathematical model is built by using the physical laws representing the asset behavior. In some cases, researchers implement a digital twin, which is a virtual replica enabling simulation of scenarios, test upgrades, and identification of potential failures before their occurrence [20,21]. Digital twins, as very accurate models, may provide close-to-life results, but marine engines are compound systems, difficult to reproduce in the digital space without approximations that can lead to wrong predictions [5,11].
- Data-driven: ML and DL algorithms are used to find relations between data [5–7,9,11]. Digital twins can be based on data-driven models and there exist hybrid methods combining model-based and data-driven approaches. In general, data-driven models can be applied using a supervised approach, an unsupervised approach, or even a semi-supervised approach. Supervision consists in exploiting data that are labeled, i.e. associated to healthy and faulty conditions. Obviously, most of the data acquired during the life of the engine are healthy. Since that, supervised algorithms are often hard to realize [6,22,23]. Then, unsupervised algorithms are often considered and trained only on healthy values [6]. Data fed to the algorithms are not labeled, so we do not know whether they are healthy or faulty, nor do we know the type, size, and severity of the fault, and we rely on AI to identify patterns in the data. Semi-supervised approaches use a small amount of labeled data along with a large amount of unlabeled data during training. Finally, another approach is reinforcement learning, which is neither supervised nor unsupervised and works by maximizing rewards.

Table 1 provides an overview of the aforementioned, main contributions to CBM, with reference to the maritime sector. However, research in other fields has also led to great advances in CBM. For example, a reference review is [24], which has described industrial process monitoring in detail and in a general way, thus providing a good basis to determine the root causes of maintenance, without limitation to a specific field of interest, e.g. marine engines. Moreover, each industrial field has its own specific way of realizing CBM, which may be unsuitable in other cases. For example, the chemical industry is experiencing great progress as is the maritime industry. Namely, the work [25] proposed a framework based on traditional correlation analysis combined with a machine learning method. Also, a Bayesian network is combined with novel machine and deep learning strategies in [26]. Other examples of AI techniques applied to complex industrial applications can be found in [27–29].

This work focuses on achieving CBM by taking advantage of data-driven models, obtained through ML and DL algorithms. In fact, this approach is attracting much interest from the industries of the field thanks to its high versatility. In case of new engines, both knowledge- and model-based methods require high efforts to build new models; on the contrary, if data are available, training new data-driven algorithms requires less time and effort. Namely, digital twins do not depend on the amount of data, but suffer the issues of complexity and reliability of the twin model [5,11]. To conclude, CBM with AI through a data-driven approach is realized by the workflow depicted in Figure 2. First, we must get the data. Then, we apply pre-processing techniques. After, we train the most suitable algorithm. Finally, we apply the algorithm to the real system.

Table 1. Classification of the most representative contributions to different approaches to CBM.

Works	Different approaches to CBM and predictive maintenance
[6,11]	Unsupervised or semi-supervised approaches
[8]	Classification algorithm
[5,12,23]	Supervised algorithms
[17]	Experts' knowledge-based approach
[20,22]	Model-based approach
[30–32]	Decision Support Systems
[33,34]	Surveys

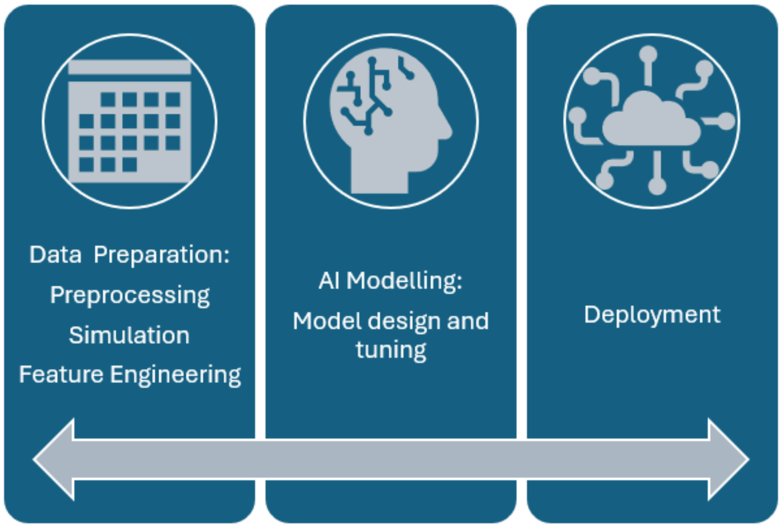

Figure 2. Condition-Based Maintenance with AI.

1.2. Paper Objective and Outline

The objective and main contribution of this work is to provide an integrated-oriented framework that unifies recent and significant fault prediction algorithms and CBM strategies using machine and deep learning algorithms. To the best of the authors' knowledge, most of the literature focuses on individual aspects of CBM, fault problems, detection algorithms, whereas our goal is to unify different prediction techniques into a single framework that takes into account all stages of CBM, from formalization to implementation. The framework should serve as an AI-based methodology for the maritime industry interested in fault prediction and CBM. We integrate AI algorithms in a unique strategy, starting with the development of algorithms capable of predicting both aging faults and catastrophic faults, and culminating in a decision support system (DSS), which should support decisions in the event of detected or predicted faults. This approach should prove particularly useful for managing the aforementioned faults through a single, integrated system, and thus for the practical implementation of CBM of marine engines.

Note that, in reality, there is no universal "one-size-fits-all" tool because the problem spans three fundamentally different domains: design (physics-based), operation (real-time control), maintenance (data-driven analytics). On the contrary, there is a class of integrated platforms that, when combined, achieve a continuous chain from design to monitoring, diagnostics, maintenance, and feedback into design. This concept exists in aerospace systems [35,36] and is increasingly adapted to maritime vehicles and systems, although less mature in this field [37–39]. The key idea is to connect design assumptions, real operational data, and maintenance decisions. Previously, health management was considered as an additional element to design rather than as a separate sub-system, fully integrated with the asset design itself [35].

Today, maritime industry has some integrated DSS platforms for CBM of onboard machinery but they are typically vendor-specific [12]. Furthermore, an innovative DSS may integrate the characteristics and functionality of predictive and detection algorithms, but is often built on assumptions and requirements proposed years ago but still valid [40,41]. These papers described the design of diagnostic and control systems by using a supervisory structure, remedial actions, etc., and the strategy to validate the systems by computing several performance indexes (time to detect faults, false detection probability, missed detection probability, etc.). To sum up, they addressed the problem of fault-tolerant control, but laid the foundations for diagnostic and prognostic systems. However, a unified framework that addresses all phases of CBM implementation is still missing, from the analysis of faults to the identification of those with higher impact, development of associated detection strategies, modeling of these strategies by advanced data-driven methods, algorithmic coding, and integration into a single platform. Then, our contribution could help bridge the gap between theory and practical realization of fault prediction and CBM of marine engines. We finally remark that the combination of ML and DL algorithms into a DSS is necessary to provide a solution useful for industry. In fact, displaying this combination through user interfaces helps human operators analyze the results of predictive algorithms and understand the state-of-the-health of the asset.

The paper is organized as follows. Section 2 provides some preliminary information on faults and decision support systems using AI to help CBM. Section 3 describes the case study, namely a marine Diesel engine. Section 4 deals with the topic of the aging fault and shows how to predict the associated degradation pattern. Section 5 gives an overview of a simulated catastrophic fault and proposes a strategy for its early detection. Section 6 proposes guidelines for the design and development of a DSS. Section 7 draws the conclusions with some future research prospects. We remark that, after the previous literature review, the following Sections 2 and 3 are the preliminary knowledge needed to address the CBM topic; then, the integrated-oriented framework is presented in Sections 4–6.

2. Preliminaries

2.1. Faults Modeling and Classification

The IFAC SAFEPROCESS Technical Committee provided a standardized, internationally recognized terminology for fault diagnosis, supervision, and safety in technical processes [42]. This terminology, largely developed by R. Isermann and P. Ballé [43–46], ensures a common language for identifying abnormal system behavior. Some of the fundamental definitions are as follows:

- Fault: an unpermitted deviation of at least one characteristic property or parameter of the system form the acceptable/usual/standard condition.
- Failure: a permanent interruption of an ability to perform a required function under specified conditions.
- Error: a deviation between a measured or computed value (of an output variable) and the true, specified or theoretically correct value.
- Residual: a fault indicator, such as a deviation between measures and model-equation-based computations.
- Fault detection: determination of the faults present in a system and the time of detection.
- Monitoring: continuous real-time determination of the conditions of a physical system, by recording information, recognizing and indicating anomalies in the behavior.

It is important to distinguish faults from failures. A fault is a deviation (unpermitted state), whereas a failure represents a permanent loss of function. Stated in other words, a fault could be the underlying cause (why). A failure is the observed result when the system fails to meet expected requirements (what). In this work, we present methods to observe and predict faults and methods to anticipate them. This is a clear benefit for industry, which can save cost of repairs if faults are predicted quite in advance.

Identifying a unique and general maintenance strategy for all possible faults in the marine engine is impossible. In fact, the engine should be protected from all the different ways in which it can fail. Since that, a crucial step in developing suitable and reliable strategies for CBM of marine engines is modeling realistic degradation patterns. They are often represented through the concept of residuals [47–56], namely the difference between the expected (healthy) values and the real sensor measurements, acquired from the monitored machines. As highlighted in [57], the degradation pattern represented by the residuals can be modeled as follows:

$$r_i(t) = F(s_i(t), \hat{s}_i(t), t) \tag{1}$$

where r_i is the residual for the i-th measured variable, s_i and $\hat{s}_i$ are the acquired and predicted sensor measurements of the i-th variable, F is the time-dependent law. F can be represented by a polynomial equation:

$$F(s_i(t), \hat{s}_i(t), t) = \sum_{l=0}^{n} a_{il}(t)\,[k_l(t)]^l \tag{2}$$

where a_{il} is the simple difference between s_i and $\hat{s}_i$, k_l is the failure coefficient, and l is the order of the polynomial equation. Based on the severity and on the degradation speed to represent, $F(s_i(t), \hat{s}_i(t), t)$ can be further detailed as an additive, multiplicative, or exponential fault.

For example, by putting $n = 1$ and $a_{i1} = 1$, a simple additive fault can be modeled:

$$F(s_i(t), \hat{s}_i(t), t) = a_{i0}(t) + k(t) \tag{3}$$

Similarly, putting $a_0 = a_1 = ... = a_{n-1} = 0$ and $l = n$, an exponential law can be obtained:

$$F(s_i(t), \hat{s}_i(t), t) = a_{in}(t)\,[k(t)]^n \tag{4}$$

Although different mathematical rules can be used to model the residuals' patterns, two main behaviors can be identified according to the degradation velocity:

- Aging fault: it is a slow and often regular pattern of degradation from a healthy to a faulty condition, mainly caused by the wear and tear and use of system components. Algorithms detecting this fault behavior must be characterized by the ability to learn and predict time-series patterns. Examples are in [9,12,57,58].
- Catastrophic fault: it is also called abrupt fault, mainly caused by mechanical problems and characterized by

a sudden and unexpected event. In fact, this fault occurs in few seconds causing the total disruption of the marine engine. Then, the algorithms trained for detection must be able to process the input data and to provide reliable outputs quickly. Examples are in [59–61].

The functioning and safety of marine engines is supervised by "onshore" and "offshore" operators, the first operating remotely, the second working on board. Onshore operators manage the correct machine functioning from a terrestrial office; offshore (or onboard) operators are crew members who are on the ship. It is clear that a single algorithm can not cover both aging and catastrophic faults. Therefore, training two different algorithms and integrating them into a unique decision support system designed to support both onshore and offshore operators is crucial to guarantee the safety of the marine engines.

2.2. Learning from Data and Taking Decisions

Choosing the most suitable ML and DL algorithms based on the fault to detect and predict is just the initial step for correct integration of the CBM strategies for marine engines. Indeed, integrating the codes implementing these algorithms into an user-friendly software system that supports both onshore and offshore operators in monitoring the marine engines is another crucial step. This software system is known as expert system [30] or decision support system [31]. It is a powerful instrument used to extract meaningful information from data acquired by sensor measurements, to help onshore and offshore operators to know the state-of-the-health of the monitored engine, and to organize maintenance audits if necessary.

Even if the focus of the current work is to apply data-driven models for CBM, all the different CBM strategies that were previously described can be integrated into DSS. For example, while artificial neural networks (ANNs) are used as basis for the DSS in [31], a knowledge-based approach is developed in [30]. Furthermore, large language models (LLMs) have been recently applied into DSS. Herein, the data-driven models for fault detection are still the core of the DSS, the difference is how data is processed and information proposed to the human user. Namely, in the case of LLMs, the DSS works as a chat-bot, waiting for user inputs to process and providing useful information as output. In more details, in the traditional DSSs, the algorithms placed in the backend of the user interface make predictions and then the predicted faults are shared with the user through alarms or labels. Whereas, in case of LLMs, the user makes queries; then, the chat-bot elaborates the query asked by the human and processes the data to give a textual output. An example is provided by [32].

We will focus on the DSS that processes the data in the backend and shows them on charts and labels, like those explained in [30,31]. In future research, the LLM-based DSS will also be considered and will be a perfect case to consider AI agents that communicate and interact to operate, monitor, diagnose, maintain, and control the entire life cycle of the marine engine.

3. The Marine Diesel Engine

In this work, a high-speed marine Diesel engine is the system under condition-based maintenance. Figure 3 shows an example of this type of engine.

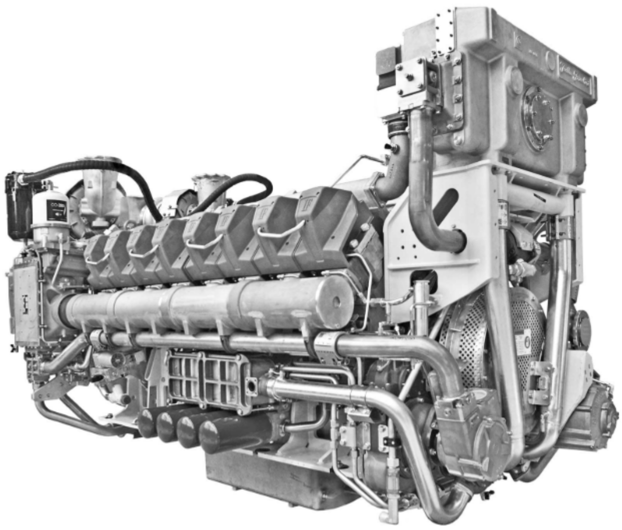

Figure 3. Marine Diesel engine (courtesy of Isotta Fraschini Motori S.p.A., see https://www.isottafraschini.it/prodotto/vl1716c2-mlh/ (accessed on 27 March 2026)).

Now, an overview of the engine parts and the main physical modeling laws are essential to understand the complexity of the system. As highlighted in different works [22,33], a traditional marine Diesel engine is often divided into four subsystems:

- air and exhaust gases circuit: it is the circuit that manages the air and exhaust gas circulation through the engine. The air is crucial for the combustion process and for providing enough energy to the turbocharger systems.
- oil circuit (also known as Lube circuit): this circuit guarantees the correct lubrication of the mechanical parts.
- water circuit (also known as the cooling circuit): it is divided into the low- and high-temperature circuits, the water is used to cool down the temperature of the mechanical components.
- fuel circuit: it is the circuit in which the fuel flows. Its main task is to correctly manage the injection to have an optimal combustion process.

A detailed description of each circuit is beyond the scope of this work. Despite that, we provide a quick overview of the mathematical modeling equations that are usually applied in the literature [20,62,63]. Basically, the considered physical laws can be reduced to the conservation of mass, energy, and momentum. Taking the (intake or exhaust) manifold as an example, the conservation of the mass can be written as follows [62]:

$$\frac{V}{R}\,\frac{d}{dt}\Big(\frac{p}{T}\Big) = \Delta m \tag{5}$$

where R is the universal gas constant, V is the manifold volume, and T and p are the gas temperature and pressure in the manifold, respectively; $\Delta m = m_{in} - m_{out}$ is the time variation of mass between the inlet and the outlet of the manifold.

Assuming time-invariance of the volume, the conservation of the energy in the manifold is written as:

$$\frac{V}{R}\,c_v\,\frac{dp}{dt} = (m_{in}\,h_{in}) - (m_{out}\,h_{out}) \tag{6}$$

where c_v is the specific heat in case of constant volume, and h_{in} and h_{ou} are, respectively, the inlet and outlet fluid enthalpy.

Similarly, in the case of engine cylinders, the conservation law of the mass is written as follows:

$$\frac{dm_{cyl}}{dt} = \Delta m + \alpha_i \tag{7}$$

where m_{cyl} is the whole mass inside the cylinder, Δm is the variation of the mass flow between the inlet and outlet valves, and α_i is the ideal burned fuel rate.

Finally, focusing the attention on the turbocharger, the dynamic equilibrium is described by the momentum equation:

$$I_T\,\frac{d\omega_{TS}}{dt} + \nu\,\omega_{TS} = \frac{\Delta P}{\omega_{TS}} \tag{8}$$

where I_T is the inertia momentum of the turbocharger system, ν is the viscous friction coefficient, ω_{TS} is the rotational speed of the turbocharger system, and, finally, ΔP is the difference between the power given by the turbocharger and the one received by the compressor.

The described equations are the basis for modeling the entire marine engine, under suitable assumptions. The reader is referred to [62,63] for more details.

4. The First Problem: Aging Fault

As remarked in the introduction, the aging faults are characterized by slow degradation patterns due to usage and wear. Since that, the algorithms trained for predicting such faults must be able to recognize and predict time-series patterns. To this aim, the most suitable algorithms are the recurrent neural networks (RNNs) and their variants, as the long short-term memory (LSTM) algorithm, defined for the first time by [64]. This is true because the memory and update cell, which is intrinsic to the LSTM algorithm (see Figure 4), allows us to manage and retain only the most useful information in the learning process and to predict data patterns. Moreover, compared to a traditional RNN, this cell avoids the so-called vanishing gradient problem, where the gradient represents the direction and the entity of the error. The vanishing gradient usually occurs while training the neural networks, during the back-propagation phase, when the gradient risks to assume values that are too small. The typical LSTM architecture is shown in Figure 4, in which the memory and forget cells are emphasized, since they increase the algorithm capabilities to manage long-term dependencies. Examples of the LSTM applied to the CBM of marine engines can be found in [5,6,9,11,58].

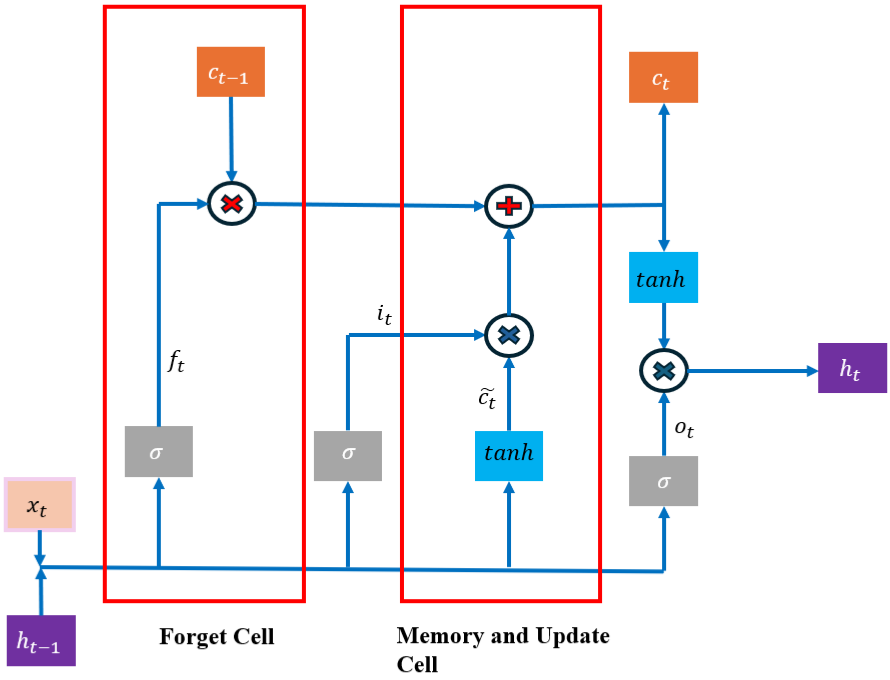

Figure 4. Architecture of the LSTM algorithm.

The discrete-time equations that describe the algorithm are the following:

$$f(t) = \sigma(W_f \cdot [h(t-1), x(t)] + b_f), \tag{9}$$

$$i(t) = \sigma(W_i \cdot [h(t-1), x(t)] + b_i), \tag{10}$$

$$\tilde{c}(t) = \tanh(W_c \cdot [h(t-1), x(t)] + b_c), \tag{11}$$

$$c(t) = f(t) \cdot c(t-1) + i(t) \cdot \tilde{c}(t), \tag{12}$$

$$o(t) = \sigma(W_o \cdot [h(t-1), x(t)] + b_o), \tag{13}$$

$$h(t) = o(t) \cdot \tanh(c_t), \tag{14}$$

where t and $t-1$ are the current and previous discrete time instants, $x(t)$ the input, $h(t)$ the hidden state, $f(t)$ the forget state, $i(t)$ the input state, $c(t)$ the cell state, $o(t)$ the output state, σ the sigmoid activation function, W denote weight matrices, and, finally, b are biases. The sigmoid function filters the useful information in the forget cell: if its value is 0, then the information is forgotten; if it is 1, then the information is kept for prediction. The memory and update cell works in a similar way, by the $\tanh$ function "deciding" the information to update. Finally, the output information is managed by the last sigmoid function.

The LSTM weights are updated by defining a loss function. Among the most common ones available in the literature for regression tasks, the root mean squared error (RMSE) is frequently used in this role:

$$\text{RMSE} = \sqrt{\frac{1}{D}\sum_{i=1}^{D}(y_i - \hat{y}_i)^2}; \tag{15}$$

where D is the number of data points, y is the real (measured) output value, and $\hat{y}$ the predicted one.

After the most suitable predictive algorithm has been chosen, i.e. the LSTM, the next step is to develop an efficient strategy to apply it. Since the goal is to predict a slow degradation pattern, the fault has been modeled as an additive fault:

$$y_{fi}(t) = y_{hi}(t) + k(t) \tag{16}$$

where y_{f_i} and y_{h_i} are the faulty and healthy values of the i-th sensor measurement y and $k(t)$ is a fault coefficient.

Then, as remarked by [65], it is important to note that the ML and DL algorithms work properly if the statistical law used for data generation does not change over time. If it changes, this is referred to as "data distribution shift" in the literature. Since that, we made the following assumption.

Assumption 1. *The engine under consideration is installed on ships with a regular and predictable behavior. These ships always travel the same route daily and cyclically.*

This hypothesis allows to consider ships that sail the same path day after day, with slow or minimal changes over time. In this scenario, the LSTM can be correctly applied. Namely, working conditions as in Assumption 1 mainly characterize ferry ships and cruise ships. These vessels follow a strictly defined route, which is highly suitable for predicting future trends in sensor measurement time series. Other approaches must be investigated for luxury or military ships. In these cases, the working conditions are not regular, highly variable, and often random and, consequently, the time series are not predictable [65]. A different possibility could be to predict the drift, that is, the difference between healthy, expected values and the values actually acquired by measurements.

Having identified the case study for marine Diesel engines with regular behavior, we develop the following multi-step methodology to train the LSTM and to correctly predict time-series of variables measured by sensors:

1. the engine is started and data are collected for a period of time of length ΔT_1 and then stored;
2. the data acquired from sensors are used for training an LSTM algorithm;
3. the trained LSTM predicts the time-series patterns for a period of time of length ΔT_2;
4. the trained LSTM predicts a second cycle of time-series patterns for a period of time of length ΔT_2;
5. the predictions and healthy sensor data are compared and the consequent fault detection is made;
6. if a fault is not detected, the LSTM waits for new data from the next period of length ΔT_1 to be retrained; if a fault is detected, an alarm is generated;
7. the oldest data are replaced with the newest ones;
8. go back to step 2.

We tested the proposed methodology with three different variants of the traditional LSTM:

- a traditional LSTM;
- an LSTM optimized by a genetic algorithm [66];
- an encoder–LSTM combination [34].

An overview of the proposed method, which is a kind of moving-window approach, is shown in Figure 5. This approach, based on an online cyclical-update logic, overcomes one of the most important limits in applying data-driven algorithms: the availability of data. In fact, here the LSTM is trained directly "on the field", without the necessity of acquiring a large amount of data offline. Moreover, deleting the oldest data and replacing them with newest data is justified by a second assumption. Note that, while the data for the initial window of length ΔT_1 is gathered to train the LSTM, the data immediately following is buffered and used in the following ΔT_2 window, where the choice of ΔT_1 and ΔT_2 is free. Moreover, since we wait before retraining, there is no overlap between the data used in successive training processes.

It is worth noting that, in the literature, the LSTM is not the only algorithm applied for CBM and prediction by time series, but it is the most suitable algorithm to detect aging faults [5]. In fact, other approaches such as ANNs are widely used to predict expected and nominal values of sensor measurements, but are not suitable for predicting future behavior, whether healthy or faulty. Moreover, literature shows the LSTM is often combined with other techniques. For example, it is often integrated into an Autoencoder to build a reconstruction algorithm, which is trained to provide an output equal to the input [11]. If the difference between the inputs and the reconstructed outputs exceeds a fixed threshold, then a fault is detected. While this technique can detect the presence of a fault in the system, it does not provide any information about its future behavior. Since the ability to provide future insights is the core of CBM, the LSTM was chosen due to its ability to learn and predict future time series. It is worth noting that other algorithms with this feature are the Gated Recurrent Unit (GRU) and the Recurrent Neural Networks (RNN), but the GRU are a simplified version of the LSTM and the RNN are inherently flawed due to the vanishing gradient problem that the LSTM structure overcomes. Then, the traditional LSTM is a good benchmark algorithm to predict aging faults.

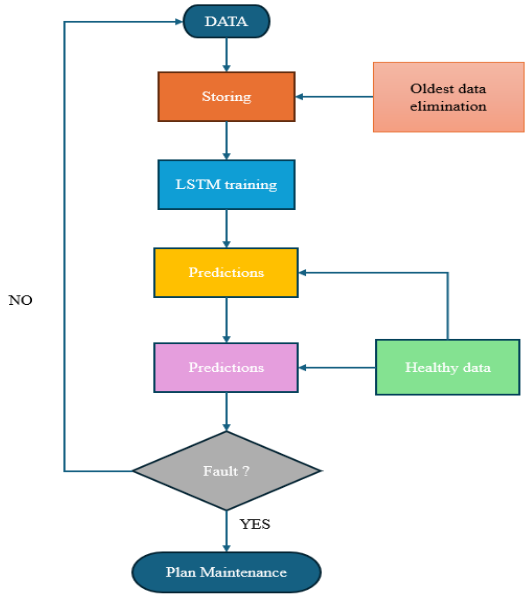

Figure 5. Method for detecting aging faults.

Assumption 2. *The fault behavior is more affected by newest data than by oldest ones.*

This assumption is intuitive, but improves the prediction. Namely, the aging law can change over time, making the acquired data obsolete.

We simulated a specific fault that is the drift of the exhaust manifold temperature. To this aim, we used a simulation model very similar to a digital twin of the engine under consideration. The results showed that the simple LSTM has the lowest percentage relative error, which is computed as:

$$E\% = \frac{\hat{y}(t) - y(t)}{y(t)} \cdot 100 \tag{17}$$

where $\hat{y}(t)$ is the predicted sensor measurement and $y(t)$ is the real one. In fact, a traditional LSTM was able to keep the error below 2% in both the presence and absence of noise, whereas the encoder combined with the LSTM showed less reliability especially in presence of noise; finally, the optimization by a genetic algorithm increased the risk of overfitting. More details can be found in [9,58]. Figure 6 shows some results that can be derived from the approach in the cited works. The green line shows the LSTM prediction of the exhaust temperature, while the orange line shows the actual value. It is clear that the proposed strategy can predict the future time series of the measured variable correctly, thus can detect any anomaly drift sufficiently ahead of time. From a practical point of view, this allows the ship owner to order spare parts and plan maintenance when strictly necessary. Moreover, unexpected downtime is avoided and safety is increased.

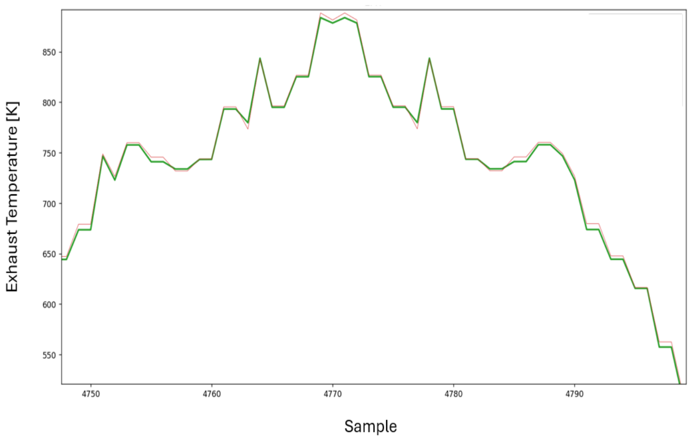

Figure 6. Aging fault detection: comparison between LSTM prediction and actual values of exhaust temperature.

5. The Second Problem: Catastrophic Fault

The next step is to develop a strategy suitable for catastrophic faults. As remarked in the introduction, a catastrophic fault is an anomaly that occurs suddenly and is impossible to predict far in advance. Then, the only possible way to manage this problem is early detection. It is important to note that detecting such a fault even just few seconds before it occurs is crucial for the marine engine. In fact, an early detection allows us to avoid unexpected power losses, consequently the ship commander can secure the vessel by altering the route if any obstacles are present, or he can raise the alarm to evacuate the engine room. Then, it is clear that detection time is the key factor in developing suitable strategies to detect catastrophic fault early. A reliable solution is to not focus on the error itself, computed as indicated in Equation (17), but to consider its first and second derivatives. Consequently, we propose the following method in successive steps:

1. Each time new data are acquired, their error is evaluated according to Equation (17);
2. The first derivative of the error (a sort of "error velocity") and the second derivative of the error (a sort of "error acceleration") are computed as:

$$v(t) = \frac{de(t)}{dt} \approx \frac{e(t) - e(t-1)}{\Delta T} \tag{18}$$

$$a(t) = \frac{d^2e(t)}{dt^2} \approx \frac{v(t) - v(t-1)}{\Delta T} \tag{19}$$

   where ΔT is the data acquisition time-step.
3. If the first and second derivatives show an increase in the density of peak values, it means that something is wrong and is suddenly happening in the engine: an alarm is triggered.

Figure 7 shows an overview of the proposed framework. A suitable algorithm to apply this approach is the decision tree (DT). In fact, it is a widely applied predictive algorithm easy to train in noisy scenarios, as the one of interest. Its structure determines a prediction process working as follows: each node gives a branch split that leads to an output or to another decision node; the first decision is taken in the input nodes, called roots; then, internal decisions, made by other nodes, determine the flow of the decision process depending on the values of input data; the leaves, representing the final decision, output the predicted values.

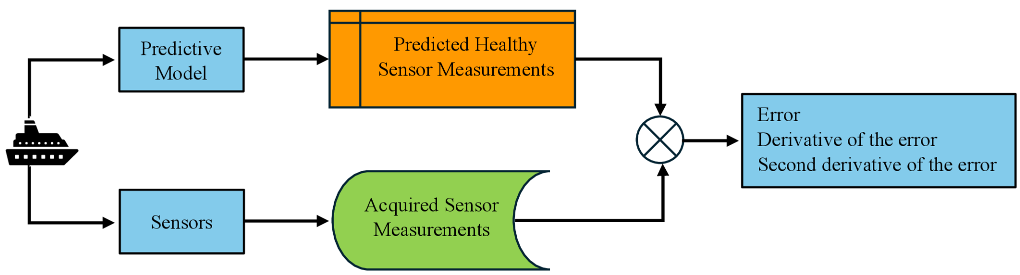

Figure 7. Method for detecting catastrophic faults.

Figure 8 shows a possible DT of the engine under analysis. In the figure, the rotational speed in rpm and the power are the DT inputs used to predict the expected sensor measurements (outputs). In details, P1, P2, P3 are power values and RPM1, RPM2, RPM3, RPM4 are speed values in different regimes; all are used by the DT to take decisions. Based on the inputs, the decision-making process follows one path or another to determine the sensor measurement predicted as output. Each different path leads to a different outcome. Note that predictions are used to compute the error to be used in (18) and (19).

The DT is trained by reducing the value of the entropy variable. It is a measure of the uncertainty level in assessing a variable in a decision process and is expressed as follows:

$$E(S) = -\sum_{x \in X} p(x)\, log_2 p(x) \tag{20}$$

where S is the dataset, X a class in the dataset S, and x a variable. The entropy has values between 0 and 1: the lower the entropy after a node decision, the more effectively the DT is trained. Then, the Information Gain and Gini impurity are the other two key variables that properly describe a DT. The Information Gain is the difference between the values of entropy

$$I(S, x) = E(S) - E(S|x) \tag{21}$$

where $E(S|x)$ is the entropy of the sample S given the assessment of x. Finally, the Gini Index is the probability of making an error in classifying a sample:

$$G = 1 - \sum_i p_i^2 \tag{22}$$

where i represents the i-th class, p_i is the fraction of elements that belong to class i in a specific node. Figure 9 shows the training of the DT associated to the considered engine. Training is made to yield sensor measurements in healthy conditions. These values are then compared to those measured in real time to get an error and then compute its derivatives. As the straight line shows, the predictions of sensor measurements under healthy conditions basically correspond to the real values.

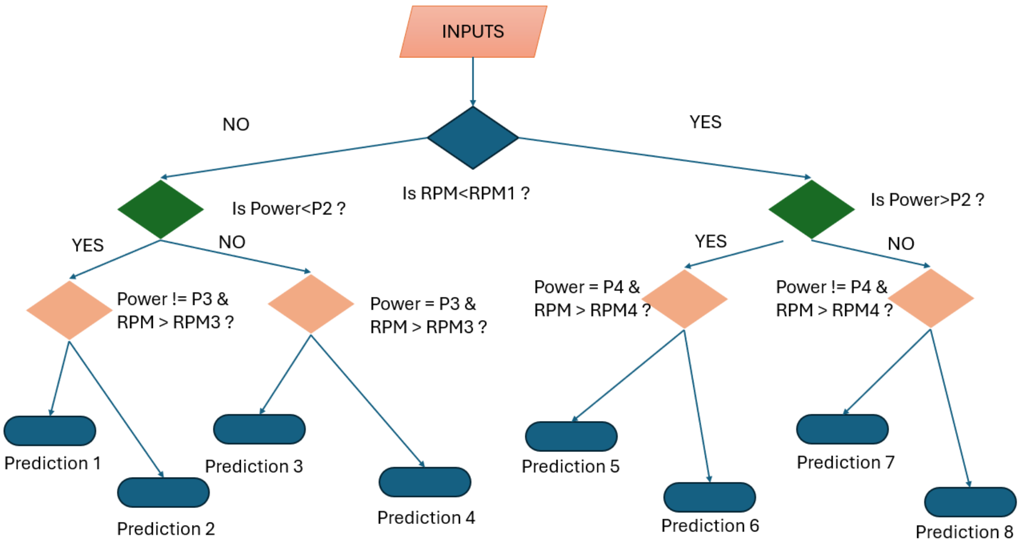

Figure 8. Decision tree for the considered marine engine.

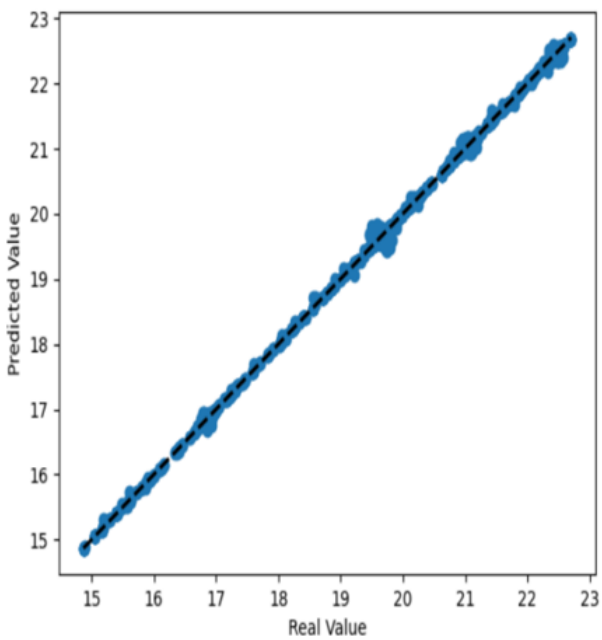

Figure 9. Training of the Decision Tree.

This approach has been tested on a simulated catastrophic fault due to a bearing collapse in a marine engine. The results showed the reliability of the proposed method, see [61] for more details. The Figure 10 shows important results derived from the approach in the cited paper. The blue and orange lines are, respectively, the first and second derivatives of the error, in its turn shown in green. The dotted line is the sensor threshold. As clearly visible, the fixed alarm threshold is exceeded by the proposed approach much earlier than by using the simple error, thereby preserving the engine integrity and lifetime, while increasing the safety of the crew and of the transported goods.

Consequently, the proposed approach shows very promising results. However, improvements are necessary.

Namely, implementation in a real-life scenario is challenging and not easy. Data coming from the asset are affected by noise, then the derivative computation shows spikes that can produce false alarms. A simple solution widely applied in industry is based on noise filters. Moreover, a threshold must be defined for detecting faults through the error derivatives. An initial choice is the threshold used for the error to detect failures in sensor measurements. Then, the threshold value can be fine-tuned by a test campaign in real conditions.

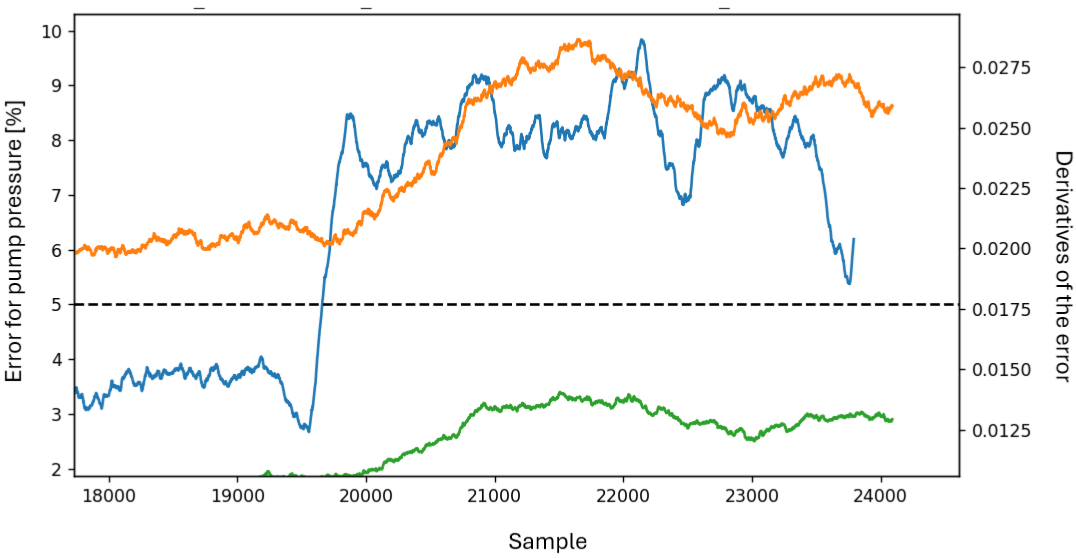

Figure 10. Error and its first and second derivatives.

6. Third Problem: Decision Support System

The last step in realizing the framework for fault prediction and CBM is to integrate the two presented predictive strategies for fault detection into a decision support system supporting onboard and onshore operators.

To address this topic, it is important to take into account that the CBM is developing a paradigm shift during the revolution brought by the Internet of Things (IoT). In fact, the development of a DSS is not a simple integration of ML and DL algorithms into a graphical user interface, but consists of integrating several tools for: acquiring and storing the sensor measurements; processing these data; using them as inputs of the predictive models; storing and further processing the outputs of the predictive models; finally, making a decision based on the obtained information. It is clear that all these data and the extracted information must be provided in real time and without or with short delay, such that the faults are detected with adequate time in advance. Since that, an automation, control, and supervision system (ACS) is often required, namely, a centralized system that manages and processes all the data and information, making decisions autonomously, without waiting for human input. Consequently, a constant cloud networking and communication between the ACS and the controlled vessels is desirable and must be guaranteed. In fact, even if a CBM technology can be installed onboard, an online cloud-based solution is often preferred. This is because in this way both onboard and onshore operators can have access to information about fault predictions, and may coordinate an emergency response in case of failures and breakdowns. This is particularly important in the case of autonomous ships, which are obviously supervised by an ACS acting if some issues occur. The choice of this cloud-based supervision system opens new challenges, especially related to cyber-security, such as the so-called adversarial attack [67]. A simplified representation is provided by Figure 11, which highlights the need, especially in the current geopolitical situation, to correctly secure the information and software tools that are stored on the cloud, the core and brain of the overall CBM system.

Addressing all the issues highlighted in this section is beyond the scope of this work, but being aware of their existence is necessary for the reader to have an overall idea of how challenging the CBM implementation is.

Focusing on the DSS design, two are its key requirements that must drive the implementation:

1. the most suitable fault prediction algorithm must be chosen;
2. the DSS must be user-friendly both for the onboard and onshore operators.

The first issue has been addressed in [7], where the authors proposed to compare predictive algorithms with a loss function, which is evaluated by combining both the prediction time and the prediction accuracy. The idea is that once all the possible algorithms available in the literature are tested, the one with the lowest loss function can be chosen.

The second problem is designing an ACS that can display only the most important and easily interpreted information to the user, preventing their attention from getting lost in unnecessary, complicated, and superfluous details. Since that, the user must be able to navigate into the DSS and easily retrieve the necessary information. In addition, the operators' attention must be maintained through high-level alarms when faults are detected or predicted. Note that information flows not only from the DSS to the user, but also from the user to the DSS. An overview of the system and the information flow is in Figure 12 and in [68].

We observe that language models can be used to streamline the human-machine interface, and AI agents can be employed to make the analysis more efficient for operators (and possibly tailor-made depending on the experience/background of the user).

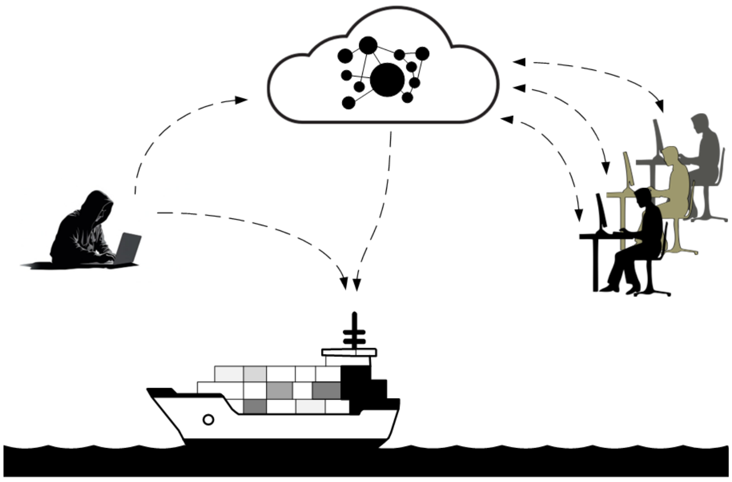

Figure 11. Challenges in DSS implementation.

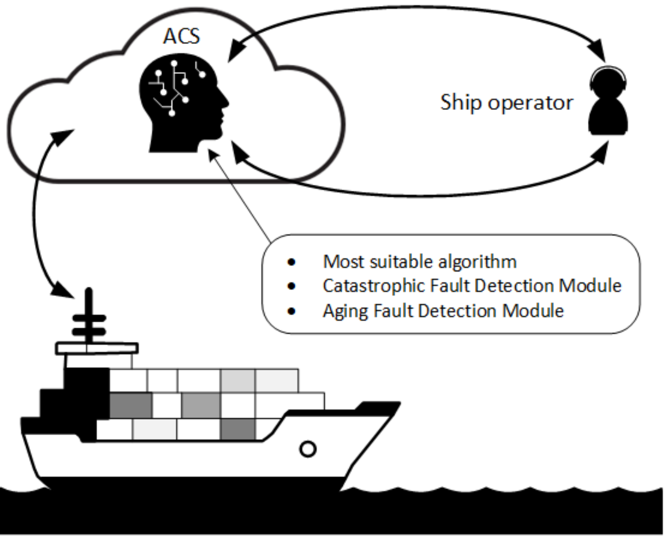

Figure 12. Information flow between ship/ACS and onshore operators.

7. Conclusions and Open Issues

This work addressed the main topics for the development of a unified framework to apply effective AI algorithms in CBM of marine engines. First, the two main types of fault that can affect the asset have been identified—the aging and catastrophic ones. Second, suitable predictive strategies have been developed. The LSTM algorithm has been chosen to predict the occurrence of aging faults in the case of ships with periodic and regular behavior, whereas the DT algorithm was chosen for fast and timely detection of catastrophic faults. Finally, the requirements and challenges of DSS implementation have been described.

Several open issues must still be addressed. In fact, as remarked in the previous sections, cyber-security is a primary characteristic in implementing CBM by an ACS [67]. Moreover, the problem of managing data coming from an entire fleet of ships is hard and still studied. In the literature, the federated learning approach was identified as a promising solution to also address customer privacy [69,70]. It consists of sharing in a common cloud not the acquired data, but only the trained models. Consequently, in the centralized cloud, an "average" predictive model is created and shared by different customers. It is an original solution that allows to remove several limitations in CBM implementation: each individual customer's data are not shared with others, thus protecting his privacy; the centralized cloud does not run a predictive model for each customer, but just one model for all customers, such that delays and computational cost are reduced.

Finally, in this work, the aging fault detection module and the catastrophic fault detection module have been independently analyzed and developed. Consequently, no communication has been designed between them. Recently, the agentic AI architecture has been introduced in the CBM paradigm [71]: it consists in the creation of an interconnected system between the different AI agents implemented. By this technique, the aging and the catastrophic modules would no longer operate passively on their own, but, thanks to a global AI agent, they would share information allowing a more effective engine management. Obviously, the aging detection agent and the catastrophic detection agent can be supported by and cooperate with other AI agents, in their turn devoted to energy management system, fault-tolerant control, and prescriptive maintenance. The computational cost will increase, but it will make a big step forward to fully autonomous ships.

Finally, the last direction for future research could be the implementation of maybe more powerful tools for CBM of marine engines, such as reinforcement learning (RL) [72,73]. This technique seeks an optimal solution by maximizing a reward function. Its strength is the fact that a RL-based approach searches autonomously for the optimal solution. Consequently, it can be easily implemented into a deep learning architecture to search for the best combination of hyper-parameters characterizing the architecture. The RL-based approach is suitable in applications where supervised learning is not possible and where a single optimal solution must be determined. This could cover many cases of marine engines and systems, especially innovative systems for which experts' knowledge is not available, like in the case of hydrogen fuel cells.

The described research activities also represent the future trends that the CBM research is going to follow. At the same time, it is worth noting that every novel algorithm or strategy must be tested in close-to-real-life scenarios. In fact, the algorithms must have a quick response, must be robust to changes in working conditions and possess high adaptability. Consequently, an algorithm should be preferred over another not only based on the predictive performance during its training, but also based on its behavior during the engine lifespan. Since that, a good trade-off between novelty and wide applicability is the key factor that must drive the CBM research.

Author Contributions

F.M.: conceptualization, formal analysis, investigation, methodology, software, validation, writing—original draft preparation; P.L.: formal analysis, visualization, writing—original draft preparation; G.G.: data curation, funding acquisition, resources; E.M.C.: formal analysis, investigation, writing—reviewing and editing; O.L.O.: supervision, writing—reviewing and editing; G.M.: conceptualization, funding acquisition, supervision, writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Funding

Activities described in this paper have been developed within the Fincantieri project "Wave 2 the Future" (W2F) funded by the European Union–NextGenerationEU. W2F project is part of IPCEI Hy2Tech.

Data Availability Statement

Data used in this research are not available due to a confidential non-disclosure agreement with Isotta Fraschini Motori S.p.A.

Conflicts of Interest

Given the role as Associate Editor, Guido Maione had no involvement in the peer review of this paper and had no access to information regarding its peer-review process. Full responsibility for the editorial process of this paper was delegated to another editor of the journal. Fincantieri S.p.A. and Isotta Fraschini Motori S.p.A. had involvement in the decision to publish the results. The authors take full responsibility for the content of the published article. The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

References

1. Angelopoulos, A.; Giannopoulos, A.; Nomikos, N.; et al. Federated Learning-Aided Prognostics in the Shipping 4.0: Principles, Workflow, and Use Cases. *IEEE Access* **2024**, *12*, 6437–6454.
2. Lazakis, I.; Ölçer, A. Selection of the best maintenance approach in the maritime industry under fuzzy multiple attributive group decision making environment. *Proc. Inst. Mech. Eng. Part M: J. Eng. Marit. Environ.* **2015**, *230*, 297–309.
3. Industry Analytics Research Consulting. Marine Engine Market—Forecast (2026–2032), Report Code: EPR 0004. Available online: https://www.industryarc.com/Report/15099/marine-engine-market.html#: ˜ :text=Furthermore%2C%20downtime%20due%20to%20engine,of%20the%20marine%20engines%20market (accessed on 31 March 2026).
4. Molland, A.F. Chapter 11—Marine Safety. In *The Maritime Engineering Reference Book—A Guide to Ship Design, Construction and Operation*; Butterworth-Heinemann: Oxford, UK, 2008; 784–875.
5. Han, P.; Ellefsen, A.L.; Li, G.; et al. Fault Prognostics Using LSTM Networks: Application to Marine Diesel Engine. *IEEE Sens. J.* **2021**, *21*, 25986–25994.
6. Ellefsen, A.L.; Bjøorlykhaug, E.; Æsøy, V.; et al. An Unsupervised Reconstruction-Based Fault Detection Algorithm for Maritime Components. *IEEE Access* **2019**, *7*, 16101–16109.
7. Maione, F.; Lino, P.; Maione, G.; et al. A Machine Learning Framework for Condition-Based Maintenance of Marine Diesel Engines: A Case Study. *Algorithms* **2024**, *17*, 411.
8. Susto, G.A.; Schirru, A.; Pampuri, S.; et al. Machine Learning for Predictive Maintenance: A Multiple Classifiers Approach. *IEEE Trans. Ind. Informat.* **2015**, *11*, 812–820.
9. Maione, F.; Lino, P.; Maione, G.; et al. Predictive Maintenance of Marine Engines using a Long Short-Term Memory Algorithm. In Proceedings of the 2024 IEEE 8th Forum on Research and Technologies for Society and Industry (RTSI), Lecco, Italy, 18–20 September 2024; pp. 578–583.
10. Langone, R.; Alzate, C.; De Ketelaere, B.; et al. Kernel spectral clustering for predicting maintenance of industrial machines. In Proceedings of the 2013 IEEE Symposium on Computational Intelligence and Data Mining (CIDM), Singapore, 16–19 April 2013; pp. 39–45.
11. Han, P.; Ellefsen, A.L.; Li, G.; et al. Fault Detection with LSTM-Based Variational Autoencoder for Maritime Components. *IEEE Sens. J.* **2021**, *21*, 21903–21912.
12. Cipollini, F.; Oneto, L.; Corradu, A.; et al. Condition-Based Maintenance of Naval Propulsion System with Supervised Data Analysis. *Ocean Eng.* **2018**, *149*, 268–278.
13. Wu, W. Predictive Maintenance: How It Works, Costs & Key Examples. Available online: https://coastapp.com/blog/predictive-maintenance/ (accessed on 27 March 2026).
14. Liang, Q.; Knutsen, K.E.; Vanem, E.; et al. A review of maritime equipment prognostics health management from a classification society perspective. *Ocean Eng.* **2024**, *301*, 117619.
15. Niazi, M.A. Predictive vs. Preventive Maintenance. Available online: https://control.com/technical-articles/predictive-vs-preventive-maintenance/ (accessed on 27 March 2026).
16. Nithin, S.K.; Hemanth, K.; Shamanth, V. A Review on Combustion and Vibration Condition Monitoring of IC Engine. *Mater. Today Proc.* **2021**, *45*, 65–70.
17. Ventikos, N.P.; Sotiralis, P.; Annetis, E. A combined risk-based and condition monitoring approach: developing a dynamic model for the case of marine engine lubrication. *Transp. Saf. Environ.* **2022**, *4*, tdac020.
18. Awang, M.N.; Zali, Z.; Mohd Noor, N.A.; et al. Main Propulsion Marine Diesel Engine Condition Based Maintenance Monitoring Using Ultrasound Signal. In *Advancement in Emerging Technologies and Engineering Applications*; Lecture Notes in Mechanical Engineering; Saw, C., Woo, T., Karam Singh, S., et al., Eds.; Springer: Singapore, 2020; pp. 175–187.
19. Haxhiu, A.; Abdelhakim, A.; Kanerva, S.; et al. Electric Power Integration Schemes of the Hybrid Fuel Cells and Batteries-Fed Marine Vessels—An Overview. *IEEE Trans. Transp. Electrific.* **2022**, *8*, 1885–1905.
20. Pagán Rubio, J.A.; Vera-García, F.; Grau, J.H.; et al. Marine Diesel Engine Failure Simulator Based on Thermodynamic Model. *Appl. Therm. Eng.* **2018**, *144*, 982–995.
21. Boschert, S.; Rosen, R. Digital Twin—The Simulation Aspect. In *Mechatronic Futures*; Hehenberger, P., Bradley, D., Eds.; Springer: Cham, Switzerland, 2016; pp. 59–74.
22. Kougiatsos, N.; Vessa, R. A Distributed Cyber-Physical Framework for Sensor Fault Diagnosis of Marine Internal Combustion Engines. *IEEE Trans. Control Syst. Technol.* **2024**, *32*, 1718–1729.
23. Jaramillo Jimenez, V.; Bouhmala, N.; Gausdal, A.H. Developing a predictive maintenance model for vessel machinery. *J. Ocean Eng. Sci.* **2020**, *5*, 358–386.
24. Ali, H.; Safdar, R.; Liu, J.; et al. Hybrid fusion paradigm in advanced process monitoring: a panoramic review and future perspectives. *Ind. Eng. Chem. Res.* **2025**, *64*, 22465–22514.
25. Husnain, A.; Rizwan, S.; Muhammad, H. R.; et al. Advance industrial monitoring of physio-chemical processes using novel integrated machine learning approach. *J. Ind. Inf. Integr.* **2024**, *42*, 100709.
26. Husnain, A.; Rizwan, S.; Jinfeng, L.; et al. Process monitoring and dynamic fusion of complex industrial systems: A reconstruction-based Bayesian framework. *Comput. Chem. Eng.* **2025**, *203*, 109352.
27. Ali, H.; Safdar, R.; Ding, W.; et al. Intelligent machine learning-based multi-model fusion monitoring: Application to

industrial physio-chemical systems. *Control Eng. Pract.* **2025**, *162*, 106361.
28. Ali, H.; Gao, F. Fault detection and diagnosis using reconstruction-based DiGLPP: application to industrial distillation system. *IFAC-PapersOnLine* **2025**, *59*, 187–192.
29. Ali, H.; Safdar, R.; Zhou, Y.; et al. A novel dynamic machine learning-based explainable fusion monitoring: application to industrial and chemical processes. *Mach. Learn. Sci. Technol.* **2025**, *6*, 015005.
30. Gharib, H.; Kovács, G. Development of a New Expert System for Diagnosing Marine Diesel Engines Based on Real-Time Diagnostic Parameters. *J. Mech. Eng.* **2022**, *68*, 642–653.
31. Karatuğ, C.; Arslanoğlu, Y.; Guedes Soares, C. Design of Decision Support System to achieve condition-based maintenance in ship machinery systems. *Ocean Eng.* **2023**, *281*, 114611.
32. Kim, Y.; Lee, K.; Han, Y. Exploring large language models (LLMs)-based chatbots for pump maintenance in ships. *Ships Offshore Struct.* **2025**, 1–19. https://doi.org/10.1080/17445302.2025.2550529.
33. Youssef, A.; Noura, H.; El Amrani, A.; et al. A Survey on Data-Driven Fault Diagnostic Techniques for Marine Diesel Engines. *IFAC-PapersOnline* **2024**, *58*, 55–60.
34. Ellefsen, A.L.; Æsøy, V.; Ushakov, S.; et al. A Comprehensive Survey of Prognostics and Health Management Based on Deep Learning for Autonomous Ships. *IEEE Trans. Reliab.* **2019**, *68*, 720–740.
35. Jennions, I.K.; Niculita, O.; Esperon-Miguez, M. Integrating IVHM and Asset Design. *Int. J. Progn. Health Manag.* **2016**, *7*, 1–16.
36. Rajamani, R.; Saxena, A.; Kramer, F.; et al. *Developing IVHM Requirements for Aerospace Systems*; SAE Technical Paper 2013-01-2333; SAE: Warrendale, PA, USA, 2013.
37. Zocco, F.; Wang, H.-C.; Van, M. Digital Twins for Marine Operations: A Brief Review on Their Implementation. *arXiv* **2023**, arXiv.2301.09574.
38. Menges, D.; Rasheed, A. Digital Twin for Autonomous Surface Vessels: Enabler for Safe Maritime Navigation. *arXiv* **2024**, arXiv:2411.03465.
39. Pang, T.Y.; Pelaez Restrepo, J.D.; Cheng, C.-T.; et al. Developing a Digital Twin and Digital Thread Framework for an 'Industry 4.0' Shipyard. *Appl. Sci.* **2021**, *11*, 1097.
40. Blanke, M.; Frei, W.C.; Kraus, F.; et al. What is Fault-Tolerant Control? *IFAC Proc. Vol.* **2000**, *33*, 41–52.
41. Izadi-Zamanabadi, R.; Blanke, M. A Ship Propulsion System as a Benchmark for Fault-Tolerant Control. *Control Eng. Pract.* **1999**, *7*, 227–239.
42. TC 6.4. Fault Detection, Supervision & Safety of Technical Processes-SAFEPROCESS. Terminology in the Area of Fault Management. Available online: https://tc.ifac-control.org/6/4/terminology/terminology-in-the-area-of-fault-management (accessed on 27 March 2026).
43. Isermann, R.; Ballé, P. Trends in the Application of Model-Based Fault Detection and Diagnosis of Technical Processes. *Control Eng. Pract.* **1997**, *5*, 709–719.
44. Isermann, R. Process fault detection based on modeling and estimation methods—A survey. *Automatica* **1984**, *20*, 387–404.
45. Isermann, R. Model-based fault detection and diagnosis—Status and applications. *Annu. Rev. Control* **2005**, *29*, 71–85.
46. Isermann, R. *Fault Diagnosis Systems—An Introduction from Fault Detection to Fault Tolerance*; Springer Verlag: Berlin/Heidelberg, Germany, 2005.
47. Patton, R.J. Fault detection and diagnosis in aerospace systems using analytical redundancy. In *IEE Colloquium on Condition Monitoring and Fault Tolerance*; IET: London, UK, 1990.
48. Frank, P.M.; Ding, X. Frequency domain approach to optimally robust residual generation and evaluation for model-based fault diagnosis. *Automatica* **1994**, *30*, 789–804.
49. Basseville, M. Information criteria for residual generation and fault detection and isolation. *Automatica* **1997**, *33*, 783–803.
50. Frank, P.M.; Ding, X. Survey of robust residual generation and evaluation methods in observer-based fault detection systems. *J. Process Control* **1997**, *7*, 403–424.
51. Patton, R.J.; Chen, J. Observer-based fault detection and isolation: Robustness and applications. *Control Eng. Pract.* **1997**, *5*, 671–682.
52. Simani, S. Identification and Fault Diagnosis of a Simulated Model of an Industrial Gas Turbine. *IEEE Trans. Ind. Informat.* **2005**, *1*, 202–216.
53. Puig, V.; Stancu, A.; Escobet, T.; et al. Passive robust fault detection using interval observers: Application to the DAMADICS benchmark problem. *Control Eng. Pract.* **2006**, *14*, 621–633.
54. Puig, V.; Quevedo, J.; Escobet, T.; et al. Passive Robust Fault Detection of Dynamic Processes Using Interval Models. *IEEE Trans. Control Syst. Technol.* **2008**, *16*, 1083–1089.
55. Serdio, F.; Lughofer, E.; Pichler, K.; et al. Residual-based fault detection using soft computing techniques for condition monitoring at rolling mills. *Inf. Sci.* **2014**, *259*, 304–320.
56. Simani, S.; Farsoni, S.; Castaldi, P. Fault Diagnosis of a Wind Turbine Benchmark via Identified Fuzzy Models. *IEEE Trans. Ind. Electron.* **2015**, *62*, 3775–3782.
57. Fang, X.; Blesa, J.; Puig, V. Fault Prognosis Approach Using Data-Driven Structurally Generated Residuals. In Proceedings of the 2024 32nd Mediterranean Conference on Control and Automation (MED), Chania, Greece, 1–14 June 2024; pp. 531–536.

58. Maione, F.; Lino, P.; Giannino, G.; et al. A New Deep Learning Strategy to Predict Time-Series of Marine Diesel Engines. *IEEE Trans. Ind. Appl.* **2026**, *62*, 2300–2310.
59. Ceylan, B.O.; Akyuz, E.; Arslanoğlu, Y. Modified quantitative systems theoretic accident model and processes (STAMP) analysis: A catastrophic ship engine failure case. *Ocean Eng.* **2022**, *253*, 111187.
60. Liu, S.; Shen, C.; Chen, Z.; et al. A sudden fault detection network based on Time-sensitive gated recurrent units for bearings. *Measurement* **2021**, *186*, 110214.
61. Maione, F.; Lino, P.; Maione, G.; et al. A Machine Learning Method to Early Detect Catastrophic Failures of Marine Diesel Engines: A Case Study. In Proceedings of the 2025 European Control Conference (ECC), Thessaloniki, Greece, 24–27 June 2025; pp. 3195–3200.
62. Dotoli, M.; Lino, P. Fuzzy Adaptive Control of a Variable Geometry Turbocharged Diesel Engine. In Proceedings of the 2002 IEEE International Symposium on Industrial Electronics, L'Aquila, Italy, 8–11 July 2002; Volume 4, pp. 1295–1300.
63. Bondarenko, O.; Fukuda, T. Development of a Diesel Engine's Digital Twin for Predicting Propulsion System Dynamics. *Energy* **2020**, *196*, 117126.
64. Hochreiter, S.; Schmidhuber, J. Long short-term memory. *Neural Comput.* **1997**, *9*, 1735–1780.
65. Makridis, G.; Kyriazis, D.; Plitsos, S. Predictive maintenance leveraging machine learning for time-series forecasting in the maritime industry. In Proceedings of the 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), Rhodes, Greece, 20–23 September 2020; pp. 1–8.
66. Holland, J.H. *Adaptation in Natural and Artificial Systems*; The MIT Press: Cambridge, MA, USA, 1992.
67. Zhuo, Y.; Yin, Z.; Ge, Z. Attack and Defense: Adversarial Security of Data-Driven FDC Systems. *IEEE Trans. Ind. Informat.* **2023**, *19*, 5–19.
68. Giannino, G.; Maione, F.; Lino, P.; et al. Digitalization of Marine Power Sources: From Theory to Practice. In Proceedings of the International Maritime Transport and Logistics Conference "MARLOG 14", Alexandria, Egypt, 23–25 February 2025; pp. 307–318.
69. Han, P.; Liu, Z.; Sun, Z.; et al. A novel prediction model for ship fuel consumption considering shipping data privacy: An XGBoost-IGWO-LSTM-based personalized federated learning approach. *Ocean Eng.* **2024**, *302*, 117668.
70. Shrestha, R.; Mohammadi, M.; Sinaei, S.; et al. Anomaly detection based on LSTM and autoencoders using federated learning in smart electric grid. *J. Parallel Distrib. Comput.* **2024**, *193*, 104951.
71. Hasan, A.; Kandemir, E.; Mordasov, D.; et al. Agentic AI in Wind Energy Systems: Multi-Agent Architectures for Optimization and Resilience. *IEEE Access* **2026**, *14*, 9935–9951.
72. Zaccaria, V.; Sartor, D.; Del Favero, S.; et al. Fault Identification Enhancement with Reinforcement Learning (FIERL). In 2024 American Control Conference (ACC), Toronto, ON, Canada, 10–12 July 2024; pp. 1494–1499.
73. Li, Y.; Wang, Y.; Zhao, X.; et al. A deep reinforcement learning-based intelligent fault diagnosis framework for rolling bearings under imbalanced datasets. *Control Eng. Pract.* **2024**, *145*, 105845.