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Review

A Review of Prognostic and Health Management (PHM) Methods and Limitations for Marine Diesel Engines: New Research Directions

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Abstract: Prognostic and health management (PHM) methods focus on improving the performance and reliability of systems with a high degree of complexity and criticality. These systems include engines, turbines, and robotic systems. PHM methods involve managing technical processes, such as condition monitoring, fault diagnosis, health prognosis, and maintenance decision-making. Various software and applications deal with the processes mentioned above independently. We can also observe different development levels, making connecting all of the machine's technical processes in one health management system with the best possible output a challenging task. This study's objective was to outline the scope of PHM methods in real-time conditions and propose new directions to develop a decision support tool for marine diesel engines. In this paper, we illustrate PHM processes and the state of the art in the marine industry for each technical process. Then, we review PHM methods and limitations for marine diesel engines. Finally, we analyze future research opportunities for the marine industry and their role in developing systems' performance and reliability. The main added value of the research is that a research gap was found in this research field, which is that new advanced PHM methods have to be implemented for marine diesel engines. Our suggestions to improve marine diesel engines' operation and maintenance include implementing advanced PHM methods and utilizing predictive analytics and machine learning.

Keywords: prognostic and health management; marine diesel engines; expert systems; new research directions

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1. Introduction

Almost 90% of global trade is carried out by 90,000 commercial ships, and despite the international trend for intelligent and eco-friendly power systems, diesel engines are still the primary power source for over 99% of commercial ships [1,2]. However, the main reasons for operating diesel engines on ships are the unpredictable changing conditions and the need for a highly flexible system that can cover all of the complicated, weather-related, and unstable conditions. Marine diesel engines are still the most reliable and efficient power source for marine vehicles. On the other hand, most alarm monitoring systems on these engines depend on operator experience and engineers' knowledge, and these experts are not always available to assess the condition and data. In addition, modern vehicles are trending toward intelligent analysis and unmanned systems, which has led to the necessity of installing advanced prognostic and health management (PHM) systems [3,4]. A proper selection of prognostic and health management systems will improve engine performance and efficiency.

Many relevant papers in the literature have been reviewed in the prognostic and health management research field. The most recent and comprehensive study was published by Peng Zhang et al. They explored a significant amount of the literature to offer a viewpoint for scientists and crucial advice for the design, operation, and maintenance of marine equipment diagnosis and maintenance systems [5]. Based on their conclusions and similar studies on different machinery systems [6,7], we explored possible applications for marine diesel engine operation and maintenance.

In a recent study, Çaglar Karatug et al. proposed that implementing intelligent algorithms for diagnosing the condition of marine diesel engines could enhance operational efficiency and reduce operational costs. To achieve this, they suggested a condition-based maintenance strategy incorporating a fault diagnostic approach based on artificial neural networks. The methodology is adaptable to various marine engines and systems on board, making it a versatile solution to prevent minor and major faults before they occur. By developing this approach, human errors in maintenance can also be reduced [1]. Jerzy Kowalski et al. suggested a new method to identify faults in four-stroke marine diesel engines. Their fault diagnosis system addresses 14 fault conditions using extreme learning machine techniques to analyze the signals from the composition of the exhaust gas [8]. Others have studied reliability and sustainability improvements depending on optimizing the maintenance strategy [9–12]. Meanwhile, Lan et al. focused on the development trend of performance prediction methods for marine diesel engines. The authors concluded, after an analysis of the literature, that the foundation of the prognostic and health management system for marine diesel engines would be the performance prediction of the entire engine and each component, supporting the development of modern ships systems [13].

Several researchers have studied the possibility of using thermal imaging to study structures' heat distribution to improve engine condition prediction and achieve a better maintenance decision process [14–17]. While Bagavathiappan et al. provided a general review of the state of the art [14], Justyna Molenda et al. studied the possible application of thermal imaging in the case of marine diesel engine turbochargers; they used an infrared camera with appropriate software to obtain the temperature distribution on the surface of a turbocharger with different loads [15]. In contrast, Jan Monieta focused on using a thermal image of the ship's pistons for internal composition engines [16]. Mojeswara R. Duduku et al. developed an expert system on JAVA; this system uses different temperature values as the input for the condition monitoring of submarine systems while benefiting from expert systems' cost-efficiency and quick data analysis advantages [17].

Xiaojian Xu et al. presented a novel model to use a belief rule-based expert system for marine diesel engines' fault diagnosis. The results showed that using the belief rule-based expert system outperformed the artificial neural network (ANN) model, support vector machine (SVM) model, and the binary logistic regression model, regarding accuracy and stability, and could effectively identify concurrent faults. The system was built to detect abnormal wear, and it depends on the Dempster–Shafer theory to analyze uncertain data [18]. Rule-based expert systems have also been used in the marine industry for accident analysis, emission-reduction monitoring, and security assessment [18].

In another review paper, Abdenour Soualhi et al. focused on prognostic methods to estimate the remaining useful life (RUL) among the PHM strategies for industrial machines [19]. The paper included a comprehensive comparison among model-based, data-driven, and hybrid approaches, indicating the specific relation between the application and the suitable approach. Separately, some researchers have studied fault diagnoses and condition-based maintenance (CBM), considering small and large data samples and focusing on the future of data-driven methods in fault prediction systems [20–22].

A few papers have studied the improvement achieved in reliability when a machine's component is equipped with a prognostic and health management system [23–27]. Other proposed methodologies support the implementation of PHM systems based on supervised and unsupervised algorithms. Supervised algorithms use labeled data to train a model. The data have input features (such as engine parameters) and corresponding labels (such as a binary label indicating whether a fault occurred). The model learns to map inputs to outputs based on these labeled data. Once trained, the model can predict the label for new, unlabeled data. Unsupervised algorithms, on the other hand, do not use labeled data.

Instead, they identify patterns and structures in the data without a specific outcome. These algorithms are used for tasks such as clustering, where the algorithm groups data points into similar clusters based on their features. These algorithms detect engines' combustion faults, wear faults, fuel injection faults, etc. [28–30]. Compare et al. elaborated a model to evaluate the increase in machines' component reliability affected by installing a PHM system [23,25]. They demonstrated that evaluating the effects of applying PHM methods to two or more components can be complex and depends on many factors, including the specific machine being monitored, the accuracy of the PHM system, and the effectiveness of the corrective actions.

Some researchers have focused on the elaboration of health indicators (HIs) for failure diagnostics and prognostics [31–33]. Most suggested extraction techniques are component-specific (gears, shafts, etc.) [31,32,34,35]. They use various signal processing techniques to extract health indicators that could be used in the defect detection of different components operating under different load conditions. One of the recent research activities was achieved by Okoh et al., who focused on optimizing the methods used in the RUL prediction of engine components condition based on the predictability, availability, and reliability of similar machines in use. Their aim was to provide solutions and better decision ability to extend component life and map degradation processes for manufacturers and users [36]. Many recent studies have focused on RUL prediction technology, which has been considered key in improving prognostic and health management systems [37–39]. RUL prediction results can optimize decision-making and save time and cost in repairing and maintaining the machines' performance [37,38].

By exploring scientific publications, we found a lot of good and high-quality papers explaining the technical processes related to prognostic and health management systems and some good review papers. In our paper, we focus on the perspective of the marine engineering industry, how the engines' technical processes have evolved in this industry theoretically and in practice, and the possibility of achieving applicable high-quality management systems supporting the operation and maintenance decisions of marine diesel engines. Mainly, we focus on the current challenges of developing an efficient and reliable system, working on the main diesel engine system using subsystems data, and the mutual effect of these subsystems on each other to improve engine performance, in addition to the potential implementation of the recent technology and findings on remaining useful life (RUL) prediction.

The paper is organized as follows: First, an illustration of prognostic and health management processes and the state of the art in the marine industry for different technical processes are presented in Section 2. Then, prognostic and health management methods and limitations for marine diesel engines are explored in Section 3. After that, we explain newly proposed directions for improving marine diesel engines' performance and efficiency in Section 4. The final part presents the paper's conclusions in Section 5.

This study aims to outline the scope of prognostic and health management methods for marine diesel engines in real-time conditions. A further aim is to propose new directions to develop a decision support tool depending on experts' knowledge to increase the reliability and efficiency of marine diesel engines and to improve this tool and its output. This will also provide valuable insights for future research and studies.

The paper's main added value is to demonstrate the theoretical state, applications, and different approaches in PHM methods for improving marine diesel engines' performance and efficiency. Furthermore, new possible research directions are proposed in order to increase the reliability and efficiency of marine diesel engines.

2. Prognostic and Health Management System Classifications

In research on ships' main engine damage, the reports and statistics published by the Swedish Club (a well-established marine insurance company) found that losses resulting from commercial ship failures made up 47% of all ship damage losses [40]. More particularly, 28% of mechanical malfunctions involved problems with marine diesel engines.

According to the report, malfunctions in marine power systems can impact navigational safety, which can result in dangerous consequences for the crew and machines on the ship [40]. According to the same report, the most common and frequent causes of damage in marine diesel engines for the 2005–2014 period were incorrect maintenance and repairs [40]. As a result, the main goal of research into prognostic and health management systems is to reach an optimal operation of the ships' main engines.

Many researchers have offered different classifications for machines' technical processes. Generally, the technical processes can be divided into the following processes: (1) condition monitoring, (2) fault diagnosis, (3) health prognosis, and (4) maintenance decision-making.

The condition monitoring process refers to the ongoing monitoring and analysis of various engine parameters (such as vibration, temperature, pressure, etc.) to detect abnormal conditions or changes that may indicate the presence of a fault or degradation.

The fault diagnosis process identifies the specific cause of a fault or abnormal condition. Fault diagnosis can be performed through various techniques, such as vibration analysis, oil analysis, and thermography, which are used to determine the specific component or system causing the problem.

Health prognosis is the process of predicting the remaining useful life of an engine or component. This process can be carried out by analyzing historical data, performing simulations and modeling, and incorporating information from the condition monitoring and fault diagnosis processes.

The maintenance decision-making process determines the best course of action to address a detected fault or abnormal condition. This process can include repairing or replacing components, scheduling maintenance or overhauls, or monitoring the engine's condition.

Together, these four concepts form a comprehensive system for managing the health and performance of marine diesel engines. This system monitors the engine conditions in real time, identifies and diagnoses faults, predicts the remaining useful life, and makes better maintenance decisions. In addition, this system can also help optimize engine performance and reduce the risk of unplanned downtime.

2.1. Prognostic and Health Management Methods for Marine Diesel Engines

2.1.1. Condition Monitoring Process

The state of the art in condition monitoring technical processes for marine diesel engines includes using various sensor technologies, such as vibration sensors, oil analysis sensors, and thermal imaging cameras, to continuously monitor the engine's condition. Data from these sensors are analyzed using advanced algorithms and machine-learning techniques to detect early signs of engine wear or failure. These outputs allow for scheduled proactive maintenance and repairs, reducing the likelihood of unexpected downtime and costly repairs. Additionally, many condition monitoring systems now include remote monitoring capabilities, allowing for real-time monitoring and the analysis of engine performance from a remote location.

Several condition monitoring systems are widely used in marine diesel engines; some of the most popular systems include:

1. Vibration analysis systems: These systems use vibration sensors to monitor the engine's condition; the collected data are analyzed using advanced algorithms to detect early signs of wear or failure. VibroSens by VibroSystM, the Vibration Monitoring System by SKF, Inc., and the Emerson AMS Machinery Manager are examples of vibration analysis systems [41]. While all three systems focus on vibration analysis for condition monitoring, their specific features, analysis capabilities, and user interfaces vary. The selection of an adequate system depends on the specific requirements, preferences, and needs of the users or organizations. These vibration analysis systems are complex systems that employ vibration sensors strategically placed on the engine to collect vibration data. The three examples employ advanced algorithms specifically designed for vibration analysis. These algorithms utilize signal processing

techniques, such as fast Fourier transform (FFT). By applying FFT to the time-domain vibration data, the system can extract the spectral components representing different vibration frequencies presented in the signal. This spectral analysis aids in identifying specific frequency patterns associated with machinery faults or anomalies. In addition, vibration systems may integrate machine learning algorithms, such as support vector machines (SVMs) or neural networks to classify vibration patterns and detect anomalies. By utilizing these advanced algorithms, the vibration analysis systems can effectively analyze the collected vibration data in real time and identify specific vibration frequencies associated with various types of machinery faults, such as unbalance, bearing wear, or shaft misalignment. These algorithms can also compare the current vibration data with predefined thresholds or baseline models to determine the severity of the detected issues.

2. Oil analysis systems: These systems use sensors to analyze the oil used in the engine, which can provide information about the conditions and components. The oil is analyzed for contaminants, wear particles, and other engine wear or failure indicators [42]. Examples of oil analysis systems include the Ferrous Wear Meter by Parker Kittiwake and the Spectro Scientific FluidScan Q1000 by Spectro Scientific, Inc. The Ferrous Wear Meter incorporates a sensor that measures the concentration of ferrous particles in the oil. This measurement helps identify the level of wear and tear occurring within the engine components. By detecting the presence of ferrous wear particles, the system can assess the condition of crucial engine parts, such as bearings, gears, and cylinders. Similarly, the Spectro Scientific FluidScan Q1000 uses a dedicated sensor to analyze the oil's chemical composition. The sensor employs infrared spectroscopy to detect contaminants, degradation by-products, and other oil-related indicators. This analysis provides insights into the oil's degradation level, contaminants (such as water, fuel, or coolant), and potential engine wear or failure indicators. These specialized sensors, integrated within the oil analysis systems, enable the identification and quantification of various parameters relating to the oil, allowing for effective monitoring of the engine's condition and the early detection of potential issues.
3. Thermal imaging systems: These systems use thermal cameras to monitor the engine's temperature. They can provide information about specific damages and an early indication of potential problems, such as overheating [14,15]. The thermal imaging system by FLIR and MarineTherm by Raymarine are examples of thermal imaging systems. These systems are designed to detect and monitor the engine's temperature using infrared technology. When an engine operates within normal temperature ranges, the thermal imaging system captures uniform temperature distributions across its components. However, when overheating occurs, certain areas or components may exhibit higher temperatures than the expected range. By comparing the temperatures obtained from the thermal imaging system with established temperature thresholds or reference values, operators can identify abnormal temperature patterns, which indicate potential overheating issues. The thermal imaging system enables the visualization of temperature variations, highlighting hotspots or areas with excessive heat emission. These hotspots can signify various problems within the engine, such as malfunctioning cooling systems, inadequate lubrication, faulty components, or restricted airflow. The early detection of overheating using thermal imaging systems allows for timely intervention and preventive measures to eliminate further damage.
4. Combination systems: Some companies offer a combination of the above-mentioned systems, which can give a complete view of the engine's health and performance [43]. Examples of combination systems include CMMS by Wartsila, MarineSense by Rolls-Royce, and ICAS, used and developed by the American Navy. The contents of these combination systems typically include vibration analysis, oil analysis, thermal imaging, and potentially other relevant monitoring techniques. By collecting data gained from different sources, combination systems enable a more comprehensive evaluation of the engine's overall health and performance. For instance, these systems

can incorporate vibration analysis capabilities to monitor and analyze vibration data, helping to detect early signs of wear or faults in the engine components. Furthermore, these systems may also have oil analysis features to analyze the condition of the oil, detect contaminants, and evaluate engine wear indicators. In addition, thermal imaging technology is commonly incorporated into combination systems, allowing for real-time temperature monitoring and identifying potential overheating issues or abnormal temperature patterns within the engine. By merging these different monitoring and analysis techniques, combination systems provide a holistic and multi-dimensional view of the engine's health, enabling operators to make informed decisions regarding maintenance, performance optimization, and fault prevention.

It is worth noting that the condition monitoring system used may vary depending on the application, the company, and the marine diesel engine model. For example, VibroSystM is a well-established company in condition monitoring, and its VibroSens system is considered one of the industry standards for marine diesel engine condition monitoring. Many marine operators use it, including commercial shipping companies, naval fleets, and offshore oil and gas operators. The VibroSens system comprises vibration sensors, signal conditioners, and a central monitoring unit. The sensors are typically installed on the monitored machinery and collect real-time vibration data. The data are then processed and analyzed by the central monitoring unit using advanced algorithms, which can detect any anomalies in the vibration patterns of the machinery. These advanced algorithms include signal processing techniques, such as filtering, Fourier analysis (including fast Fourier transform), wavelet analysis, time-frequency analysis, and envelope analysis. In addition, it is possible to utilize machine learning algorithms for condition monitoring, such as support vector machines (SVM), neural networks, and random forest. The condition monitoring system is also equipped with various diagnostic tools, such as time waveforms, spectra, and phase analyses, which help to pinpoint the source of any detected problems. Table 1 demonstrates the most commonly used condition monitoring systems for marine diesel engines and the analysis algorithms used for each kind of condition monitoring system with current commercial software products.

Table 1. Condition monitoring systems for marine diesel engines.

Condition Monitoring System	Applied Analyses and Algorithms	Commercial Software Products
Vibration analysis systems	Time-frequency analysis; envelope analysis; order analysis; spectrum analysis; machine learning algorithms (neural networks, decision trees, clustering algorithms).	VibroSens by VibroSystM, Inc.; Vibration Monitoring System by SKF, Inc.; Emerson AMS Machinery Manager.
Oil analysis systems	Particle counting; viscosity analysis; spectroscopy; ferrography; trend analysis; machine learning algorithms (neural networks, decision trees, clustering algorithms).	Oil analysis System by Parker Kittiwake, Inc.; Spectro Scientific FluidScan Q1000 by Spectro Scientific, Inc.
Thermal imaging systems	Temperature measurement; thermal mapping; temperature Trending; image processing; machine learning algorithms (neural networks, decision trees, clustering algorithms).	Thermal Imaging System by FLIR, Inc.; MarineTherm by Raymarine, Inc.
Combination systems	These systems use a combination of sensors, such as vibration sensors, oil analysis sensors, thermal imaging cameras, and other sensors.	CMMS by Wartsila; MarineSense by Rolls-Royce; ABB Ability Marine Advisory System; ICAS, used and developed by the American Navy.

2.1.2. Fault Diagnosis Process

The state of the art in fault diagnosis techniques for marine diesel engines includes traditional methods, such as visual inspections and vibration analysis, and advanced techniques, such as statistical and machine learning algorithms, signal processing, and sensor data fusion. These techniques can detect and diagnose various mechanical, electrical, and combustion-related faults. Some of the latest research in this area has focused on using data from various sensors, such as vibration, temperature, and pressure sensors, to improve the accuracy and efficiency of fault diagnosis [44,45]. Additionally, condition-based monitoring and predictive maintenance techniques have become increasingly common in marine diesel engine fault diagnosis [46].

It can be noted that condition monitoring systems' outputs of abnormal conditions can be used as input for the fault diagnosis process. The two processes are connected to provide a comprehensive view of the engine's health and performance and to help diagnose and fix faults quickly and accurately.

Currently, there are several fault diagnosis systems used on marine diesel engines, including:

1. Vibration analysis: This system uses sensors to measure the engine's vibration and compares it to normal vibration patterns to detect abnormalities that could indicate a fault. One example of a vibration analysis system is the VibroSense Meter, which uses accelerometers to measure the engine's vibration and compares it to normal vibration patterns to detect abnormalities that could indicate a fault, such as misalignment, imbalance, or bearing wear [41].
2. Oil analysis: This system analyzes the oil used in the engine to detect contamination or other issues that could indicate a fault. One example of an oil analysis system is the ferrograph, which analyzes the oil used in the engine to detect contamination or other issues, such as metal particles and wear, which could indicate a fault [42].
3. Thermography: This system uses infrared cameras to detect changes in temperature on the engine that could indicate a fault. An example of a thermography system is the FLIR thermal imaging camera, which uses infrared cameras to detect changes in temperature on the engine that could indicate a fault, such as overheating, coolant leakage, or insulation defects. The most important advantage of these systems is that it does not need any prior preparation to start the process [14–17].
4. Acoustic analysis: This system uses microphones to detect abnormal sounds from the engine that could indicate a fault [47]. An example of an acoustic analysis system is SoundEye, which uses microphones to detect abnormal sounds from the engine, such as knocking valve noise, which could indicate a fault, such as abnormal combustion, damaged bearings, or other mechanical issues.
5. Condition monitoring systems: These systems are advanced and integrate various sensors and algorithms to monitor the engine's health and performance in real time. One example of a condition monitoring system is the ABB Ability OCTOPUS Marine Advisory System. This advanced system integrates various sensors and algorithms to monitor the engine's health and performance in real time, allowing for the early detection of potential issues and proactive maintenance. Regarding its features and capabilities, the ABB Ability Marine Advisory System is the most comprehensive and advanced compared to other fault diagnosis systems. It includes multiple diagnosis methods, provides a comprehensive view of the engine's health and performance, and includes features such as remote monitoring [48]. Other examples include the CoCoS Engine Diagnostic System of MAN [49] and DICARE of Caterpillar [50]. Both systems use data such as the engine speed, temperature, pressure, and fuel delivery rates to identify any potential issues with the fuel injectors, pumps, sensors, and other engine components. The Wärtsilä Integrated System for Energy Management (WISE) [51] is an energy management system that provides real-time monitoring and control of a ship's energy systems. It monitors fuel consumption, engine efficiency, and emissions and recommends optimized energy usage and reduced operating costs. The

Kongsberg Integrated Monitoring System (K-IMS) is an integrated monitoring system that provides real-time data and analysis for ship operators. It monitors various ship systems, including engines, generators, propulsion, and navigation, and provides alerts and notifications when anomalies or potential issues are detected [8].

2.1.3. Health Prognosis Process

The health prognosis of marine diesel engines typically involves using advanced sensors, machine learning, and data analysis to predict and prevent issues before they occur [52]. The following figure demonstrates the three stages of health prognosis [5]. Figure 1 shows the statistical time-domain equations that can be used to calculate the health indicators' values.

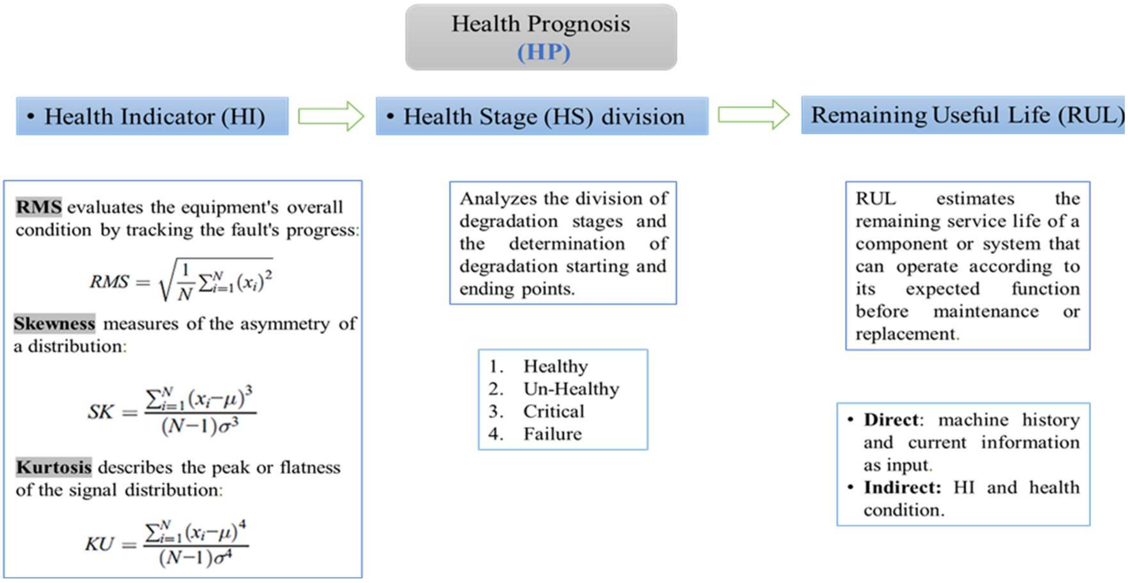

Figure 1. Health prognosis stages [5].

The three stages of machine health are closely related. If the unhealthy stage is detected early, it is often possible to take corrective actions to restore the machine to the normal stage and avoid critical failure. Regular monitoring and maintenance can help detect and address faults before they become critical. Therefore, the machine health prognosis process aims to keep the machine operating in the normal stage as long as possible and extend its remaining useful life [53].

1. *Construction of Health Indicator (HI)*

The health indicator (HI) is a scalar value that represents the health state of a mechanical component or machine. Health indicators are defined by selecting relevant features to monitor the system's health [32]. The selection of features is based on the physical condition of the mechanical component, its failure modes, and the available sensors [5]. Health indicators are typically constructed using time-domain, frequency-domain, and time–frequency-domain features. The time-domain method is commonly used when the health indicators are based on analyzing the amplitude and behavior of signals in the time domain. In this approach, statistical measures and characteristics of the time waveform are utilized to derive relevant features for assessing the health state of mechanical components or machines. The frequency-domain method is employed when the health indicators rely on analyzing the spectral content of signals. The frequency components of the signals are examined by converting the time-domain signals into the frequency-domain using techniques such as Fourier transform. Frequency-domain features are derived from the amplitude and phase information at different frequency bins or bands. The time–frequency-domain method combines the advantages of both time-domain and frequency-domain analyses by capturing the time-varying spectral characteristics of signals. This approach suits situations where the health indicators must capture transient or evolving phenomena over time. These features provide insights into dynamic changes and variations in the health condition of mechanical components or machines.

In summary, the choice of the time-domain, frequency-domain, or time–frequency-domain method depends on the nature of the signals, the required information about the health state, and the specific characteristics of the mechanical components or machines being monitored. Each domain offers distinct information and analytical capabilities, allowing for a comprehensive evaluation of the system's health condition. Table 2 presents the techniques used for HI calculations with related equations [31,32].

In general, constructing a suitable health indicator requires the following steps [34,35].

1. Selection of features: The first step in constructing a health indicator is to select relevant features to monitor the system's health. Examples of features that can be used include vibration measurements, temperature measurements, oil analysis, and acoustic measurements.
2. Feature extraction: Once the selected features are extracted from the sensor data, this step involves processing the sensor data to extract relevant information that can be used to construct the HI. Signal processing techniques may include filtering, Fourier transforms, and wavelet transforms.
3. Identify the most relevant features: After the features are extracted, the next step is to select the most relevant features to construct the HI. This step involves using methods such as principal component analysis, mutual information analysis, and correlation-based feature selection to select the most informative features.

The HI can be used to classify the health state of a component or system into different health stages, which can be used to predict when maintenance is needed and to schedule it proactively [53]. By exploring the literature [32–34], we noticed that the selection process for any method or technique to be applied to any component or subsystem depends on the type of data obtained: time-domain, frequency-domain, or time–frequency domain.

It can be observed that the time-domain health indicators are a set of metrics used to evaluate the condition and performance of machines over time. These indicators are obtained from analyzing signals generated by the machines during their operation. By monitoring and analyzing these signals, engineers and technicians can identify patterns that can help predict potential failures or other problems [31]. Furthermore, the frequency-domain health indicators are based on the frequency-domain analysis of vibration signals, which involves decomposing the signals into their constituent frequency components and analyzing the amplitudes and phases of these components [31,33]. Moreover, the time-frequency domain health indicators involve decomposing the vibration signal into its constituent time-frequency components and analyzing their energy and distribution over time. Time-frequency domain health indicators are useful for identifying specific time-frequency patterns associated with machine components and detecting any changes in the spectral signature that may indicate potential faults [31,33].

2. *Health Stage (HS) Division*

The health stage (HS) is the classification of a health condition of a machine component or system based on the value of the health indicator [32]. The health stages are defined by dividing the range of possible values of the HI into several intervals, each representing a different health condition. The division of the range of possible values of the HI into intervals is based on the condition of the system, the failure modes of the system, and the available sensors. The main idea behind this division is to divide the HI values into different intervals, each representing a different health state.

Table 2. Health indicator calculation techniques [32–34,54].

HI Construction Method	Techniques	Calculation Methods	Nomenclature
Time domain	Descriptive statistics	$CF = \frac{max\lvert x\rvert}{RMS}$ Peak of a distribution, which is important for understanding the overall shape of the distribution and the central tendency of the data; peak to peak: The difference between the maximum and minimum values of the time domain.	*CF*: crest factor; *RMS*: root mean square; *x*: time domain; x_i: *i*-th point from the time domain with length *N*; *KU*: kurtosis is the measure of the "tailedness" of the probability distribution of a real-valued random variable; σ: standard deviation; μ: time sample mean; *SK*: skewness is the measure of the asymmetry of the probability distribution of a real-valued random variable about its mean; *NA4*: normalized autocorrelation; furthermore, the "4" refers to the fourth statistical moment of the residual signal; *N*: number of points in the time domain; r_i: *i*-th point in the time domain of the residual signal; r_{ij}: *i*-th point in the *j*-th time domain of the residual signal; *M*: number of current time signals; $\bar{r}$: The mean of the residual signal; *FM4*: fourth-order figure of merit; *D*: mean of the difference signal; d_i: *i*-th signal; $K_f(f)$: spectral kurtosis; $K_x(f)$: SK of a given signal; *p(f)*: noise-to-signal ratio; *E(t)*: envelope of the BP signal; *BP(t)*: band-passed filtered signal; *H*[*BP(t)*]: Hilbert transform of BP signal; *x(t)* is the signal, *h(t)* is the window function, $X_t(\omega)$ is the STFT, and $P_{sp(t,\omega)}$ is the calculated spectrogram of the given signal as a function of time; h_i: Hilbert marginal spectrum; a_i: amplitude; f_i: instantaneous frequency.
	High-order statistics	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2}$ Delta RMS: the difference between two consecutive RMS values. $KU = \frac{\sum_{i=1}^{N}(x_i-\mu)^4}{(N-1)\sigma^4}$ $SK = \frac{\sum_{i=1}^{N}(x_i-\mu)^3}{(N-1)\sigma^3}$	
Frequency domain	Residual signal	$NA4 = \frac{N\times\sum_{i=1}^{N}\left(r_i-\bar{r}\right)^4}{\left\{\frac{1}{M}\sum_{j=1}^{N}\sum_{i=1}^{N}\left(r_{ij}-\bar{r}_j\right)^2\right\}^2}$	
	Difference signal	$FM4 = \frac{N\sum_{i=1}^{N}(d_i-D)^4}{\left[\sum_{i=1}^{N}(d_i-D)^2\right]^2}$	
	Spectral kurtosis	$K_f(f) = \frac{K_X(f)}{[1+p(f)]^2}$	
	Envelop analysis	$E(t) = \sqrt{(BP(t))^2 + H[BP(t)]^2}$	
Time–frequency domain	Short-time Fourier transform (STFT)	$P_{sp(t,\omega)} = \lvert X_t(\omega)\rvert^2 = \left\lvert\frac{1}{\sqrt{2\pi}}\int e^{-j\omega\tau}x(\tau)h(\tau-1)d\tau\right\rvert^2$	
	Hilbert–Huang transform (HHT)	$h_i(t) = \int a_i^2(f_i,t)dt$	

There are several methods for dividing the range of possible HI values into intervals, including [55,56]:

1. Expert knowledge: This method defines the intervals based on the system's condition and failure modes.
2. Statistical methods: This method involves using statistical methods, such as clustering or principal component analysis to divide the range of possible HI values into intervals.
3. Data-driven methods: This method involves using machine learning algorithms, such as decision trees, random forests, and neural networks to divide the range of possible HI values into intervals.

Once the range of possible HI values has been divided into intervals, each interval represents a different health condition. The health stage can predict when maintenance is needed, and it can be scheduled proactively.

3. *Remaining Useful Life (RUL) Prediction*

Remaining useful life (RUL) is a concept used in the field of prognostics and health management (PHM) to quantify the expected time until a machine or component will no longer function as expected based on its current condition and operating environment. The RUL is typically defined as the time interval between the current time and the point of functional degradation or failure [3]. There are several approaches to predicting the remaining useful life of a component or system, including [37]:

1. Statistical-based RUL prediction: This approach uses statistical models to estimate the remaining useful life of a mechanical component. These statistical models are based on the historical data of the component and can be used to estimate the remaining useful life even if the mechanical component has not failed yet.
2. Physics-based RUL prediction: This approach uses the physical laws that describe the mechanical component's operation to estimate the remaining useful life. These physical laws are based on the system's condition, the failure modes, and the available sensors.
3. Data-driven RUL prediction: This approach uses machine learning algorithms to estimate the remaining useful life of a component. These models are based on the historical data of the component, and they can be used to estimate the remaining useful life of a component, even if the component has not failed yet.

It is worth mentioning that reliability theory and remaining useful life prediction are related concepts in the field of prognostics and health management and are used to predict the machine's performance over time. Reliability theory provides a framework for quantifying the probability of failure or success over time based on a statistical analysis of historical data and models of the underlying failure mechanisms. Reliability analysis is typically used to estimate the probability of failure at a specific point in time or over a given time interval [57].

Remaining useful life prediction, on the other hand, is concerned with estimating the expected time until the machine or the mechanical component will no longer achieve its intended function based on its current condition and operating environment. RUL prediction is typically based on the analysis of sensor data, historical data, and other information and the behavior over time, and aims to provide accurate and timely information to support maintenance and decision-making processes. RUL prediction starts with calculating the health indicators values and then mapping the change with these values over time. After that, the division stage starts, and each condition is defined as being in a healthy, unhealthy, or failure mode. The last stage contains reading these plots and making decisions about the current condition [58].

In summary, reliability theory studies how systems and components perform over time and aims to predict the probability of failure. Remaining useful life prediction is a specific application of reliability theory that aims to predict the remaining time until failure.

According to the literature, out of the datasets used for RUL prediction, only 24.14% (28 papers) concerned operational datasets (real conditions data). The datasets were retrieved from different sources, including NASA (36.02%) and the PRONOSTIA Platform (24.13%). Only (0.86%) were about the marine diesel engine data (operational data) used to estimate the RUL values of its components, and the rest varied among experimental datasets, simulations, and testing platforms [58].

It is worth noting that the real cost of using remaining useful life prediction in terms of computational needs, the time-consuming effort, or even the model development time (study and programming) for old or new engines may be the main reason for the low application of RUL techniques on marine diesel engines. This was one of our concerns at the end of our study.

According to the literature, the challenges involving RUL prediction are as follows [58,59]:

1. Data extraction: This refers to the difficulty of obtaining high-quality data that accurately represent the operating conditions and health status. It can be challenging to collect enough data from different sources and ensure that they are reliable, complete, and representative of the entire operational range.
2. Similar conditions for training and testing: To accurately predict the RUL, it is important to have training and testing datasets that are similar in terms of the operating conditions and degradation patterns. This can be challenging in practical applications, where operating conditions vary widely, and the degradation mechanisms may differ among different components.

3. Data pre-processing and uncertainty: Data pre-processing involves transforming the raw data into a suitable format for analysis. This can be time-consuming and requires domain expertise. Additionally, there may be uncertainty in the data due to measurement errors, missing values, or other factors, which can affect the accuracy of the RUL prediction.
4. Health indicator construction complexity: Choosing and constructing appropriate health indicators that accurately represent the degradation condition can be challenging. This involves selecting and combining various features, defining appropriate thresholds, and accounting for the effects of different operating conditions.
5. Multiple operating conditions: In practical applications, machines may operate under a wide range of conditions, affecting their degradation patterns and RUL. Considering the multiple operating conditions can be challenging, as it requires large amounts of data and complex modeling techniques for each operation mode.
6. Feature selection: Choosing appropriate features to represent the health condition can be challenging, especially when dealing with big data. Feature selection techniques are used to identify the most relevant features for RUL prediction.
7. Dealing with chronological order and temporal correlation: Health-monitoring data are typically collected over time, and there may be temporal correlations among different features. Considering these correlations and the chronological order of the data is important for accurate RUL prediction.
8. Failure data availability: In some cases, failure data may be limited or unavailable, making it challenging to predict the RUL accurately. This can be handled using accelerated testing techniques or by incorporating expert knowledge into the RUL prediction.
9. Prediction interpretability, uncertainty, and accuracy: RUL prediction can be complex, and it can be challenging to interpret the outputs and assess their accuracy. Additionally, there may be uncertainty affecting the predictions.

2.1.4. Maintenance Decision-Making Process

The maintenance decisions for marine diesel engines while operating are typically made by the ship's crew based on several factors, which are the following [60–63]:

1. Condition of the engine: The crew monitors the health and performance of the engine using condition monitoring systems and other sensors and makes maintenance decisions based on the engine's condition. These systems can include scheduling regular maintenance or performing repairs and replacements as needed.
2. Risk of failure: The crew assesses the risk of failure for each component and makes maintenance decisions based on the level of risk. This step can also include scheduling regular maintenance or performing repairs and replacements as needed.
3. Maintenance schedule: The crew follows a maintenance schedule based on the manufacturer's recommendations and industry standards. This schedule includes regular maintenance activities such as oil changes, filter replacements, and inspections.
4. Real-time alerts: The crew receives real-time alerts from the monitoring system about the engine's performance and any possible issues. The crew can immediately prevent failure or scheduled maintenance activities based on these alerts.
5. Proactive maintenance recommendations: The crew receives proactive maintenance recommendations from the monitoring system, which can help to improve the reliability and efficiency of marine diesel engines and reduce the risk of unplanned downtime.
6. Cost and benefits of maintenance: The crew considers the costs and benefits of different maintenance options and selects the most cost-effective solution that will keep the engine running safely and efficiently.

The maintenance decision-making process of marine diesel engines can be improved in several ways:

- Using advanced monitoring systems such as condition monitoring systems, predictive maintenance systems, and prognostic systems will enable the crew to make more efficient maintenance decisions [64,65];

- Implementing data-driven methods to analyze large amounts of data from the monitoring systems to identify patterns and trends that can be used to predict when maintenance is needed;
- Incorporating expert engineers and technicians to make more efficient maintenance decisions based on the condition of the system, the failure modes, and the available sensors;
- Implementing a risk-based maintenance strategy to assess the risk of failure for each component and schedule maintenance based on the level of risk [66];
- Automating the maintenance process to reduce human error and improve the efficiency of the maintenance process [67];
- Incorporating remote monitoring to receive real-time alerts and proactive maintenance recommendations and monitor the engine performance and maintenance schedules [68].

3. Prognostic and Health Management Methods and Limitations for Marine Diesel Engines

Several methods can be used to make predictions and diagnoses in marine diesel engine prognostic and health management, including model-based, knowledge-based, and data-driven methods [69]. Model-based methods rely on mathematical models based on physical and engineering principles, while knowledge-based methods use expert knowledge and experience. On the other hand, data-driven methods use large amounts of data to make predictions and diagnoses. Each method has its advantages and limitations, and the method selected depends on the specific requirements and constraints of the application, such as the availability of data and the complexity of the system being modeled. Ultimately, the most effective approach may involve combining these methods. Figure 2 summarizes the currently used method for building a technical process for marine diesel engines.

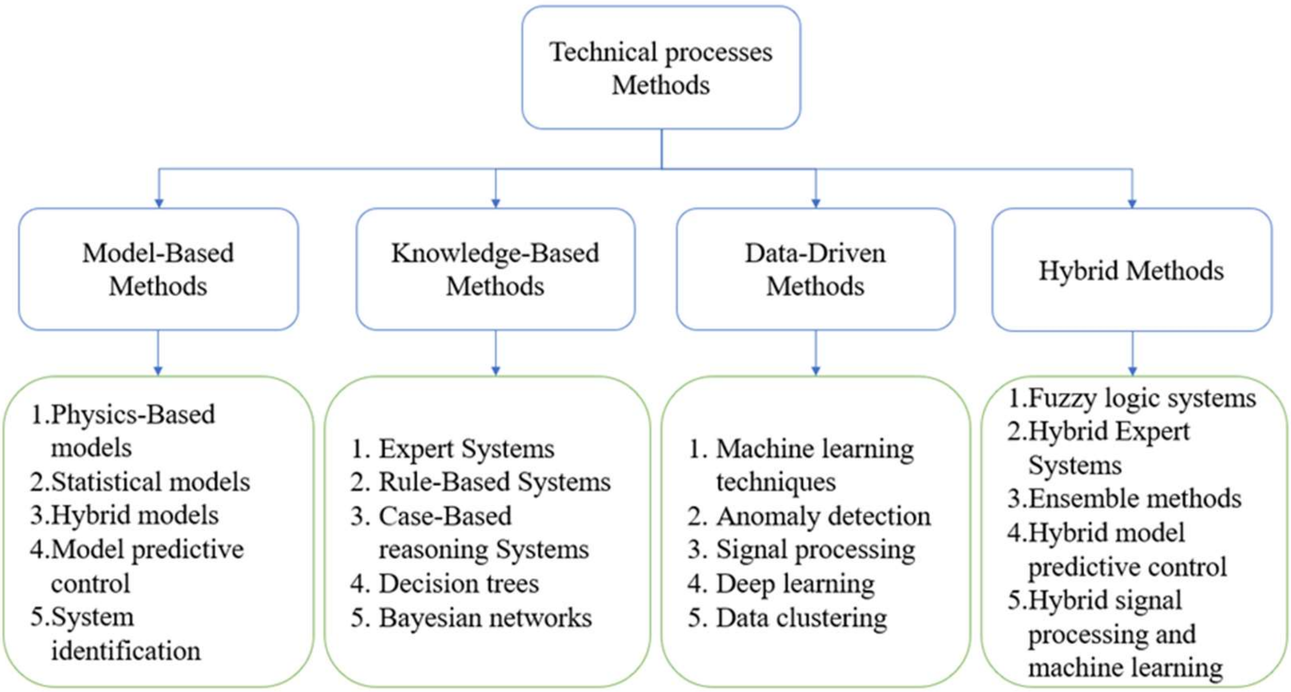

Figure 2. Technical process methods.

3.1. Model-Based Methods

Using a model-based method for building a health management system for marine diesel engines is advantageous. It allows for a more accurate and efficient diagnosis of engine problems. This is due to the use of mathematical models to represent the behavior of the engine and its components. These models can be used to simulate and predict the engine's performance under different conditions. This method can help improve the overall understanding of the engine and its behavior, identify potential problems before they occur, and reduce downtime for maintenance.

Many researchers built model-based systems to predict the performance of marine diesel engines. Kökkülünk et al. [70] used a model that reflected the effects of parameter changes on fuel consumption rate; some of these parameters are injection pressure and time, scavenging pressure, and temperature, in addition to using the baseline migration method to obtain the degradation curve. This curve can be used to identify and monitor engine performance and make informed decisions about maintenance and repair. However, the accuracy and reliability of the degradation curve depend on the quality of the data collected and the methodology used to create the baseline model.

Other authors suggested a performance simulation model based on a zero-dimensional mixing controlled combustion model. The model can predict performance characteristics using various injection rules [71]. Monieta presents an example of a thermal model for the temperature dependence of the injector body function on the relative load of the combustion engine. The thermal model could predict potential fire risks in maritime systems caused by temperature growth and catastrophic breakdowns in controlled areas [17].

One of the limitations of using model-based methods is that it requires a significant amount of data and expertise to develop and validate it. Their accuracy depends on the quality of the data used to train it and the assumptions made about the system. In addition, it can be challenging to develop models that can accurately represent the complex dynamics of marine diesel engines, especially if the data availability is limited or the system is poorly understood. This issue can lead to model inaccuracies, affecting their ability to detect problems. Another limitation is that a model-based approach may not detect certain types of problems not represented in the model, such as unexpected failures or rare weather-related conditions, because models are based on assumptions about the system. If these assumptions are not achieved, the model may be unable to detect the problem.

In summary, a model-based approach to building a health management system for marine diesel engines can provide a more accurate and efficient diagnosis of engine problems. Still, a significant amount of data and expertise are required to develop and validate the models; they also have some limitations, which have been observed in previous studies where models have been developed for a particular type of diesel engine. The models must be calibrated using a particular diesel engine's scale specification. Therefore, generalizing the approach to various diesel engines is challenging.

3.2. Knowledge-Based Methods (Expert Systems)

One advantage of using a knowledge-based method for building a health management system for marine diesel engines is that it can provide a more intuitive and easy-to-understand diagnosis of engine problems. This is because a knowledge-based method relies on a database of pre-existing knowledge about the engine and its components. This database can be used to diagnose problems based on symptoms and past experiences [15,18]. This method can help reduce the time and resources needed for maintenance and improve the overall understanding of the engine and its behavior. These systems use various decision-making techniques, including rule-based reasoning, fuzzy logic, case-based reasoning, and machine learning. The rule-based technique is one of the most widely used techniques for building expert systems. It is designed to solve problems by applying a set of rules and knowledge representations in the form of "if–then" statements. Even though traditional rule-based expert systems lack flexibility (once an expert system is built, it cannot learn from real operating data or adjust to meet changing environments), limited knowledge acquisition is considered to be the challenge of rule-based expert systems [18].

There are six common types of expert systems: rule-based, case-based, framework, fuzzy logic, neural network, and genetic algorithm [72]. Rule-based expert systems use a set of rules to draw inferences and provide advice, while case-based expert systems use past cases to solve new problems. The framework-based expert system uses a structured framework to organize knowledge and problem-solving strategies. Fuzzy expert systems deal with imprecise and uncertain information. Neural network systems simulate reasoning, and genetic algorithm systems use a genetic algorithm to find optimal solutions [72,73].

One of the limitations of using a knowledge-based method is that it relies on the accuracy and completeness of the knowledge database. If it is not up-to-date or lacks information about a particular problem, the system may be unable to diagnose it accurately. In addition, knowledge-based methods may not be able to detect new or unexpected problems, as these types of problems may not be represented in the database, which can affect the accuracy of the diagnosis. In addition, maintaining and updating the knowledge database can be time-consuming and resource-intensive, as new information about the engine and its components needs to be constantly added to the database [73].

In summary, a knowledge-based method for building a health management system for marine diesel engines can provide a more intuitive and easy-to-understand diagnosis of engine problems, with both quantitative and qualitative information.

3.3. Data-Driven Methods

A data-driven method to build a health management system for marine diesel engines uses engines' data to predict and diagnose their health. The data can be used to train machine learning algorithms, such as decision trees, artificial neural networks, or support vector machines, to predict the engine's performance, identify patterns and correlations in the data, and diagnose problems [20–22]. With enough data, data-driven methods can make highly accurate predictions and diagnoses and use the data to identify patterns and correlations, leading to improved predictions about the engine's future performance [74].

One limitation is that data-driven methods require large amounts of data to be effective. Obtaining sufficient data may be challenging, especially if they need to be collected from various sources. In addition, the data quality can greatly affect the accuracy of the predictions and diagnoses. If the data are uncertain, it can lead to incorrect predictions and diagnoses.

In conclusion, there are several advantages to using data-driven methods for building a health management system for marine diesel engines. These include high accuracy and improved predictions. However, there are also several limitations to consider. These include the need for large amounts of data, as well as the quality and accuracy of the data. Additionally, the complexity of the models used in data-driven methods can be a limiting factor. Finally, there is also the risk of overfitting, which can result in models that perform well on training data but fail to generalize to new data. Careful consideration and management of these limitations are important to ensure that a data-driven method is effective and efficient for a particular application, such as predictive maintenance, fault detection and diagnosis, and performance optimization.

3.4. Hybrid Methods

Hybrid methods combining model-based, knowledge-based, and data-driven methods are often used to build a technical system for better accuracy and robustness [5,19]. For example, the system can use a model-based approach to identify potential problems, a knowledge-based approach to apply domain expertise and provide solutions, and a data-driven approach to continuously improve the diagnosis performance through learning from historic data. It depends on the specific problem, the data availability, and the goals of the technical system.

Table 3 summarizes the advantages and limitations of the previous three main types of methods—model-based methods, knowledge-based methods, and data-driven methods—and hybrid methods.

Table 3. The advantages and limitations of the PHM methods.

Methods	Advantages	Limitations
Model-based methods	Improved accuracy; increased efficiency; improved understanding.	Complexity in mathematical modeling and simulation; model limitations, such as not representing all relevant conditions; data quality and accuracy affect building and validating the models; implementation challenges when integrating them with existing software and applications in real-time conditions.
Knowledge-based methods	Intuitive diagnosis; expert knowledge; reduced downtime.	Reliance on a knowledge database; lack of flexibility; limited ability to detect new or unexpected problems; modifying and developing the knowledge database.
Data-driven methods	High accuracy; improved predictions; increased efficiency; increased ability to customization.	Big data availability; data quality; data quality and accuracy affect building and validating the models; model complexity to represent all the conditions and process all collected data; overfitting.
Hybrid methods	Combines the strengths of different methods, leading to improved accuracy and robustness; flexible and adaptable to different scenarios, as the choice of method can be customized to the specific problem, data availability, and aim of the technical process.	More complex than individual methods, as it requires the integration and coordination of different methods; require significant resources, including expertise, time, and data, to build and maintain the system.

Despite their advantages, PHM methods have other limitations, especially for marine diesel engines. Marine diesel engine prognostic and health management system limitations currently include the following [3,5,13,19,32]:

1. Lack of standardization: There is a lack of standardization in the data collected and the methods used for analysis, which makes it difficult to compare the performance of different software and applications [75]. For example, different marine diesel engine manufacturers may use different sensor configurations and data formats, making it difficult for a prognostic system developed for one engine to be applied to another without significant modification.
2. Limited sensor availability: Many marine diesel engines do not have sensors installed to collect data on key performance indicators, which limits the ability of prognostic systems to predict and diagnose engine failures accurately. For example, an older marine diesel engine may not have sensors to measure the key performance indicators, such as the cylinder or oil pressure. Without these data, a prognostic system could not accurately predict and diagnose engine failures.
3. Difficult handling the non-linear and non-stationary systems: Marine diesel engines are complex systems that exhibit non-linear and non-stationary behavior, making it difficult to predict and diagnose failures accurately. For example, marine diesel engines can be affected by various external factors, such as the sea state and load changes, which can cause the engine behavior to change and become non-linear or non-stationary.
4. Data quality and pre-processing: The quality of the data and pre-processing can affect the performance of prognostic systems; if the data are not accurate and complete, it can lead to inaccurate or unreliable predictions and diagnoses. Similarly, if the

data are not cleaned and pre-processed properly, it can lead to unreliable predictions and diagnoses.

5. Cost-benefit analysis: Prognostic systems may be costly to implement and maintain, and the benefits may not always outweigh the costs, particularly for older or less critical engines. For example, it may not be cost-effective to implement a prognostic system on an older or less critical engine that is nearing the end of its service life.
6. Frequently changing the environmental parameters: Environmental parameters, such as the temperature, air pressure, and humidity, directly affect the engine operation and the combustion process. The frequently changing temperature can lead to variations in the fuel ignition timing, combustion efficiency, and emission levels. Similarly, changes in the air pressure and humidity affect the air–fuel mixture, which influences the engine performance and combustion dynamics. Monitoring and analyzing these parameters makes it possible to detect deviations from optimal conditions and identify potential faults or performance issues. Furthermore, the fuel used in marine diesel engines, particularly heavy oil, is more crucial to prepare and use. The fuel properties, such as the viscosity, sulfur content, and impurities, can impact fuel combustion, combustion stability, and the formation of deposits or fouling in the engine components. These factors can contribute to decreased engine efficiency, increased emissions, and potential wear or failure of critical engine parts. Considering the fuel characteristics in fault diagnosis allows for a comprehensive evaluation of engine health and helps identify fuel-related issues. Accurate fault diagnosis for marine diesel engines plays a vital role in achieving optimal results; it is crucial to integrate the monitoring and analysis of the environmental parameters and fuel characteristics. By including the temperature, air pressure, humidity, and fuel property data in the diagnostic algorithms or expert systems, it becomes possible to correlate variations in these parameters with observed faults or anomalies. This link will help in identifying potential causes, distinguishing between normal tolerances and abnormal conditions, and improving the overall accuracy of fault diagnosis.

4. New Research Directions for the Prognostic and Health Management of Marine Diesel Engines

4.1. Development of a New Hybrid Expert System for Marine Diesel Engines

Hybrid expert systems combine two or more different types of expert systems [76]. Expert systems have proven to be valuable tools in engineering, as they can provide accurate and efficient solutions to complex problems related to design, manufacturing, and maintenance processes. By benefiting from the advantages of three types of expert systems, namely rule-based, framework, and fuzzy logic, and relying on human expertise, experiments, previous observations, and sampled data, we can develop a unique expert system. This system has the potential to improve the reliability and efficiency of marine diesel engines' operation and maintenance. The expert system consists of multiple concurrently activated subsystems, which work together to provide a comprehensive and accurate diagnosis of engine problems. By using this system, we can quickly and efficiently identify issues and provide solutions, thereby reducing downtime and maintenance costs.

There are no available research studies in which the rule-based inference methodology has been applied to ship engine performance monitoring to support improving efficiency, maintenance decision-making, and fault diagnosis. Unlike traditional "if–then" rules, each output attribute of a rule is linked with a certainty degree; this certainty degree is calculated depending on normalizing the years of expertise with a range [0–1] (different from traditional certainty factor calculations). Experts can use their subjective knowledge to build an initial rule-based dataset. In order to accurately reflect the non-linear relationship between the inputs and outputs, the model's parameters can be optimized using numerical data and testing the benefits of using changeable range-based inputs instead of specific values to improve the system's flexibility.

After that, it is possible to expand and optimize the knowledge base, analyzing the effects of the engine load and speed on the diagnostic parameters and studying the change in the optimal combination of the engine's operating parameters based on previous results.

4.2. Application of Remaining Useful Life Prediction to Marine Diesel Engines

The main challenge for marine diesel engines' RUL prediction is the complexity of the system and work environment, in addition to the diversity of the operating conditions. The process of RUL prediction, accompanied by a few challenges, could be generalized as follows:

1. Data extraction involves extracting basic data from the marine diesel engine and pre-processing the data to ensure they are in a suitable format for further analysis. This can involve filtering, normalization, and other techniques [74].
2. Feature extraction and classification: Once the data have been extracted and pre-processed, the next step is to extract relevant features and classify them into different categories. This process may also include constructing a health indicator, which combines multi-dimensional features extracted from the time, frequency, and time–frequency domains into only one health indicator through dimension reduction approaches [77,78].
3. RUL evaluation: The final step in RUL prediction is evaluating and estimating the remaining useful life of the engine based on the extracted features and health indicators [78].

Despite the success of RUL prediction in other industries, such as machinery, electronics, vehicles, and aviation, there are limitations to applying RUL prediction to marine diesel engines. These limitations include the variability of ship performance due to differences in manufacturing. In addition to the need for appropriate construction and division methods, another limitation is the reluctance of ship owners to invest in RUL prediction software development due to high costs [79,80]. However, with the advancements in sensor technology, the collection of degradation signals will become more abundant, making data-driven and fusion RUL prediction methods a good possibility for development in the future.

4.3. Development of a New Advanced Software Concept That Integrates the Traditional Expert Systems and Simulation Software Applications

The ongoing development of existing expert systems for marine diesel engines has benefited greatly from advancements in the field of information technology. With the increasing availability of powerful computing hardware and sophisticated software tools, the process of upgrading expert systems has become much more streamlined and efficient.

One way to develop expert systems for marine diesel engines is through the use of advanced modeling and simulation software. One example of this software is GT-SUITE software, which is a system-level simulation tool for engine and powertrain development [81]. This software allows for the creation of detailed models of the engine and its components, which can be used to simulate and analyze various scenarios and conditions. Using such software, engineers can test different strategies and identify potential problems in a virtual environment before implementing changes in the real system. This can save time and resources and improve the accuracy of the expert system development process. These tools allow developers to create accurate representations of the engine and its components, which can be used to test and refine the performance of the expert system.

In addition, the development of new data processing and machine learning algorithms has made extracting meaningful insights from large datasets easier, which is critical for the successful development of expert systems. By analyzing data from various sensors and sources, developers can identify patterns that can be used to improve the accuracy and reliability of the expert system.

Finally, developing user-friendly applications and interfaces has made it easier for operators and technicians to interact with the expert system and interpret its outputs. By presenting information in a clear and concise style, these applications can help improve decision-making and increase the effectiveness of the expert system in maintaining and managing marine diesel engines.

5. Conclusions

Prognostic and health management (PHM) methods are used to improve the performance and reliability of complex and critical systems. This paper outlines the scope of PHM methods for marine diesel engines in real-time conditions.

The study demonstrated the theoretical state, applications, and different approaches of PHM methods for improving marine diesel engines' performance and efficiency. We proposed new possible research directions that harmonize with marine diesel engines' operation and characteristics. We described PHM methods for marine diesel engines and provided valuable insights for future research and studies.

The main added value of our research is that three possible new directions were elaborated to develop a decision support tool based on experts' knowledge to increase the reliability and efficiency of marine diesel engines, which is a complex task requiring a comprehensive understanding of marine diesel engines and current applications and developments in prognostic and health management.

A research gap was found in this research field, i.e., new advanced prognostic and health management methods have to be implemented for marine diesel engines. These new advanced methods will improve the operation and maintenance of marine diesel engines. The first possible new research direction is the development of a new hybrid expert system that combines three types of expert systems to provide a comprehensive and accurate diagnosis of engine conditions, which can reduce downtime and maintenance costs. The second possible new research direction is the application of remaining useful life (RUL) prediction on marine diesel engines, which involves data extraction, feature extraction and classification, and RUL evaluation to estimate the remaining useful life of the engine. The third possible new research direction is the integration of multiple software packages in expert systems' development for marine diesel engines, which involves using advanced modeling and simulation software, data processing and machine learning algorithms, and user-friendly applications and interfaces to improve decision-making and increase the effectiveness of the expert system.

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