Prognostic and Health Management for Marine Diesel Engines

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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. Researchers 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.

Keywords: prognostic and health management ; marine diesel engines

1. Introduction

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 [1]. 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 [1]. 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 [1]. 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. Prognostic and Health Management Methods for Marine Diesel Engines

2.1. 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:

- 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 [2]. 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.

- 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 [3]. 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.

- 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 [4][5]. 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.

- 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 [6]. 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.

2.2. 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 [7][8].

Additionally, condition-based monitoring and predictive maintenance techniques have become increasingly common in marine diesel engine fault diagnosis [9].

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:

- 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 [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 [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 [4][5][10][11].

- Acoustic analysis: This system uses microphones to detect abnormal sounds from the engine that could indicate a fault [12]. 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.

- 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 [13]. Other examples include the CoCoS Engine Diagnostic System of MAN [14] and DICARE of Caterpillar [15]. 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) [16] 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 [17].

2.3. 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 [18].

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 [19].

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 [20]. The selection of features is based on the physical condition of the mechanical component, its failure modes, and the available sensors [21]. 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.

In general, constructing a suitable health indicator requires the following steps [22][23].

- 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.

- 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.

- 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 [19]. By exploring the literature [20][22][24], researchers 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 [25]. 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 [24][25]. 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 [24][25].

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 [20]. 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.

There are several methods for dividing the range of possible HI values into intervals, including [26][27]:

- Expert knowledge: This method defines the intervals based on the system's condition and failure modes.

- 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.

- 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 [28]. There are several approaches to predicting the remaining useful life of a component or system, including [29]:

- 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.
- 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.
- 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 [30].

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 [31].

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 [31].

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.

According to the literature, the challenges involving RUL prediction are as follows [31][32]:

- 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.
- 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.
- 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.
- 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.

- 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.

- 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.

- 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.

- 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.

- 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.

2.4. 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 [33][34][35][36]:

- 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.

- 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.

- 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.

- 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.

- 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.

- 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 [37][38];

- 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 [39];

- Automating the maintenance process to reduce human error and improve the efficiency of the maintenance process [40];

- Incorporating remote monitoring to receive real-time alerts and proactive maintenance recommendations and monitor the engine performance and maintenance schedules [41].

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