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Review

Marine Systems and Equipment Prognostics and Health Management: A Systematic Review from Health Condition Monitoring to Maintenance Strategy

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Abstract: Prognostics and health management (PHM) is an essential means to optimize resource allocation and improve the intelligent operation and maintenance (O&M) efficiency of marine systems and equipment (MSAE). PHM generally consists of four technical processes, namely health condition motoring (HCM), fault diagnosis (FD), health prognosis (HP), and maintenance decision (MD). In recent years, a large amount of research has been implemented in each process. However, there is not any systematic review that covers the technical framework comprehensively. This article presents a review of the framework of PHM in the marine field to fill the gap. First, the essential HCM methods, which are widely observed in the academic literature, are introduced systematically. Then, the commonly used FD approaches and their applications in MSAE are summarized, and the implementation process of intelligent methods is systematically introduced. After that, the technologies of HP have been reviewed, including the construction of health indicator (HI), health stage (HS) division, and popular remaining useful life (RUL) prediction approaches. Afterwards, the evolution of maintenance strategy in the maritime field is reviewed. Finally, the challenges of implementing PHM for intelligent ships are put forward.

Keywords: marine; condition monitoring; health management; prognostics; fault diagnosis

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1. Introduction

With the development of modern technology, the level of ship automation and intelligence is gradually improving, and then the O&M technology for MSAE is facing new problems. The ship alarm monitoring system (AMS) relying on human experience and knowledge can no longer meet the condition assessment requirements by maintenance engineers. The traditional ship maintenance modes characterized by corrective maintenance (CM) and planned maintenance (PM) have gradually highlighted the disadvantages of "over repair" and "missing repair" lead to the increasing of ships' operation costs. With the advancement of comprehensive equipment monitoring, assessment, diagnostics, and prognostics technology, the PHM of MSAE based on a more proactive maintenance strategy has gradually become a new trend of intelligent O&M.

Currently, based on the perfect situ monitoring and advanced analysis methods, PHM technologies, approaches, and applications are developing rapidly. Its application objects gradually expand to military, aerospace, ships, and so forth. There are some representative PHM systems in these fields, such as PHM system for F-35 aircraft, AHM system for helicopter, IVHM system for spacecraft, and ICAS and PEDS system for ships [1], and so forth. At present, PHM technology has been widely studied and popularized in FD and HP of marine diesel engines and rotating machinery. The PHM of the marine diesel engine was established, and the performance prediction was realized [2]. Various applicable data and suitable technologies were integrated for engine PHM [3]. Lee et al. presented a comprehensive review of the PHM design for rotary machinery systems, followed by introducing a systematic design methodology and converting multivariate data to abstract prognostics information [4].

Modern MSAE is a complex system composed of mechanical, electrical, and hydraulic systems, consisting of interrelated subsystems, equipment, and components. Exception of any component may result in changes in health conditions. A viable PHM system framework provides condition monitoring, early fault detection, and isolation of any node in the system. The outcome of an effective PHM model provides a tool to monitor the health condition and help make O&M decisions. It is more urgent for intelligent and unmanned ships to realize the PHM to improve the integrated management of HCM, health assessment, FD, performance prediction, and maintenance implementation.

The PHM solutions of MSAE mainly cover a complete process (Figure 1), from capturing the data, information, and knowledge (DIaK) up to utilizing the results for decision-making (in maintenance, operation management, life cycle optimize control, system design, etc.).

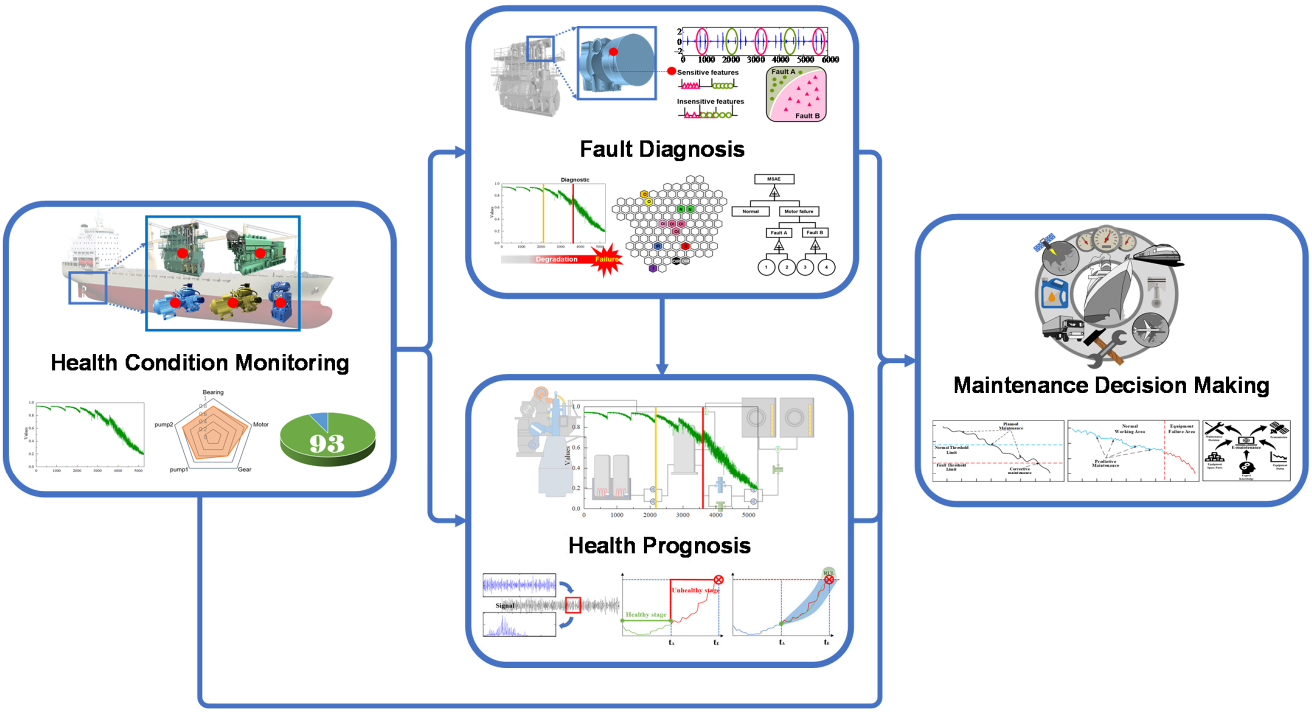


Figure 1. Relationship diagram of four parts of PHM.

A technical list of each process is shown in Table 1. At first, HCM process is to obtain ship condition parameters, realize real-time online monitoring of the mechanical system, and complete condition assessment and anomaly detection. The HCM consists of three basic processes, data acquisition, data processing, and condition monitoring. With intelligent technology and modern sensing technology, vast amounts of ship data are being collected. The data collected on-board involve navigation, MSAE condition perception, and environmental data. Data processing should first ensure the data's accuracy and integrity, and then extract and deduce valuable and meaningful data for health management from a large number of possibly disordered and complex to understand data. Condition monitoring realizes early warning, alarm and anomaly detection according to online data. Then, based on the abnormal problems of HCM, FD focuses on the failure modes and their causes and demonstrates the relationship between the monitoring data and the fault condition. After that, the realization of HP is to obtain the failure data of mechanical system through HCM and FD, and then establish the degradation model to complete the life prediction. This part focuses on the evolution of the fault process and estimates the future behavior through the necessary models to realize the failure risk assessment and change of control strategy. The HP program generally consists of HI construction, HS division, and RUL prediction. Finally, MD is done according to the results of HCM, FD, and HP. An MD describes the O&M vision of how to maintain the health and safety of assets in a whole life cycle.

Table 1. Technical list of each process.

Technical Processes	Constitution	Description
HCM	• Data acquisition • Data processing • Condition monitoring	HCM is to use various monitoring data, information, and knowledge to realize the monitoring and assessment of MSAE health conditions.
FD	• Fault feature selection • Fault diagnosis model • Fault description	FD exhibits an important role in demonstrating the relationship between the HCM information to the health condition.
HP	• HI construction • HS division • RUL method	HP aims to predict the RUL of machinery based on the historical and ongoing degradation trends observed from HCM information.
MD	• Corrective maintenance • Preventive maintenance • Predictive maintenance • Proactive maintenance	MD is to consider the coordination of health and safety of assets from a management perspective in the whole life cycle.

This paper aims to systematically review the methods, strategies, and application of MSAE in prognostics and health management. We set three keywords for searching the relevant kinds of literature, such as ship, marine, and mechanical systems. A systematic search is undertaken for the specific words combined with the methods and strategies in the four processes of HCM, FD, HP, and MD in the article title, abstract, and keywords. The search period is mainly from 2010 to 2020, and the search source is Web of Science. We excluded the papers of biology, navigation, chemistry, and port navigation in the marine fields. Some related articles with similar characteristics to MSAE are also included in the scope of discussion. A total of more than 300 articles have been retained through the processes.

There are also some excellent review papers related to PHM of ship mechanical system. For example, Rao et al. [5] provided a review on the online condition monitoring and self-repairing techniques for in-service marine diesel engine. Xie et al. [6] reviewed different blade fault types and current blade fault detection methods. Cipollini et al. [7] mainly focused on data-driven models and gave a review on the problem of performing Condition-Based Maintenance for naval propulsion systems. However, these papers just reviewed the technical processes and lacks a systematic review covering the whole program of the PHM about its advancements in recent years. A review still leaves a blank space to cover the PHM framework comprehensively in the maritime domain systematically. In order to overcome the shortcomings above, this article systematically reviews the research status and future development trend of PHM in the marine field. Compared with the existing review papers, the contributions of this review are detailed below.

(1) This article reasonably divided the whole PHM system of MSAE into four functions: HCM, FD, HP, and MD;

(2) An exhaustive review was given on the PHM technology by analyzing and summarizing a large number of references to provide a perspective for researchers and essential guidance for designers and O&M engineers;

(3) Various technologies and applications of PHM in the marine field were summarized;

(4) In order to meet the needs of intelligent ships for PHM, five new health management technologies were proposed, omnidirectional condition perception, DIaK integrated coding technology, treatment of uncertainty problems, proactive perception, and engineering self-healing and immune system.

This paper is organized as follows. Section 2 discusses the HCM. Section 3 summarizes the existing FD technology in the marine field and focuses on the application of intelligent machine learning diagnosis technology. In Section 4, the HP is discussed, including processes and methods. Section 5 concentrates on the maintenance strategies and reviews the commonly used approaches and metrics. Section 6 discusses the future challenges of PHM as well as opportunities for MSAE. Conclusions are drawn in Section 7.

2. Health Condition Monitoring

HCM is a means to monitoring MSAE health conditions through measurement condition parameters (such as temperature, pressure, level, and so forth, acquired from various sensors installed on the MSAE), external sensors data, and information. The foundation of PHM is HCM, which provides basic health condition information for the following three processes.

2.1. Data Acquisition

A data acquisition system comprises data acquisition devices, signal processing and transmission equipment, and data storage devices [8]. The data acquisition terminal is mainly composed of various sensors to obtain MSAE state parameters through various sensing methods. This data can reflect the failure evolution and performance degradation process of the system effectively. The most widely used signals of measurement sensors on-board include temperature, pressure, voltage and current, speed, and so forth. The obtained parameters are transmitted to the central data processing unit (server) according to specific coding and communication protocol. The data are further classified, processed, and stored for various analyses. With the rapid development of sensing and measurement technology, more and more intelligent condition perception methods have been proposed, designed, and applied to modern ships.

2.1.1. Data Collection

The data collected on-board involve navigation, MSAE, ship status, and environment data, which are used as condition parameters to realize the PHM process of HCM, FD, HP, and MD. Some researchers have attempted to research marine machinery performance using the measurement parameters [9].

(1) The navigation (bridge) data affecting the health condition of MSAE mainly include speed, drafts, rudder angle, and wind speed. Some of these data can be obtained directly from sensors, such as wind speed, draft, and so forth. Some of them come from the received external information, such as meteorological data, GPS data, and so forth. These navigation data are usually used as the condition or identification mark of MSAE health mode judgment, and some of them can also be used as the input of the model for more accurate decision-making [10];

(2) MSAE parameters include sensor measurement data, recorded manual data, experimental data, mooring test data, sea trial data, and so forth. The measuring sensors mainly include the sensors provided by the equipment and the sensors configured by the system integration. Due to different equipment manufacturers, the equipment usually has different data interfaces, and some data are not output. The manually recorded data

are directly read from the instrument, recorded, and stored by the engineers. At present, various test data are mainly used to facilitate comparison and query so that engineers can further understand the performance and use of equipment [7]. These data can provide training samples for FD and failure prognostics to improve the efficiency of PHM.

The application of intelligent sensors and sensor networks will maximize the acquisition of MSAE condition information and provide effective support for intelligent O&M [11]. ABS issued a guidance note to help guide intelligent technology applications in the maritime domain [12]. Through the implementation of intelligent monitoring, more operation and status information can be leveraged to support and improve daily operations and be the foundation of a PHM program [13].

2.1.2. Data Transmission

According to the data transmission mode and spatial location, the transmission mode could be divided into local data transmission and remote data transmission.

(1) Local data transmission

Local data transmission is to transmit the collected data to the monitoring system and send it to the local storage unit through various transmission modes, such as CAN bus [14], ZIGBEE wireless transmission [15], Ethernet [16], and so forth, to facilitate the completion of control, monitoring and data management. These three ways can be single and also be combined to enhance the flexibility and scalability of the data transmission. CAN bus has the characteristics of high transmission rate, high reliability, simple line, and so forth, which can be easily implemented in the engine room. Ethernet communication is easier to build a network on ships with Ethernet wiring than CAN bus. The ZIGBEE wireless transmission can solve the problem of ship wiring difficulties to a certain extent;

(2) Remote data transmission

Remote data transmission uses maritime satellites, offshore base stations, and other communication facilities to achieve data transmission from ship to shore. Data stored on the ship are transmitted to the land data center by transmission technologies (as shown in Table 2) that will be selected by the company [17]. Usually, the company completes the selection according to the communication cost and the urgency of data.

In recent years, the cost of satellite communication has gradually decreased. With the application of maritime broadband, remote data transmission is no longer the main influencing factor of ship-to-shore communication. Some ships have been able to realize the transmission of video data.

Table 2. Remote data transmission technologies.

Communication Technology	Communication Features	Scope of Application
Universal mobile communication network.	Low communication cost and large network bandwidth; small coverage and low network security.	Suitable for inland rivers and offshore ships.
Automatic identification system (AIS)	Can directly realize the speed measurement navigation function of ship positioning and monitoring and carry out information broadcasting; high service cost, seriously affected by electromagnetic environment interference, communication distance is limited.	Suitable for inland rivers and offshore ships.
Maritime satellite	Can provide data link for ocean-going ships; high cost, low communication bandwidth, maximum speed is only 492 Kbps.	Suitable for global navigation ships.
Spread spectrum communication technology	Strong concealment and good anti-interference performance; the system uses a wide frequency band and has a limited data transmission rate and distance.	Suitable for inland rivers and offshore ships.
GPS	Accurate positioning and strong anti-interference ability.	Only applicable to ship positioning, unable toachieve communication.
BDS	All-weather, all-day, high-precision positioning; short message communication has low cost and high	Suitable for global navigation ships.

2.1.3. Data Storage

Through the gateway, all the measured and processed parameters are stored in a local server. The storage time of all data stored in a database or files depends on the model and application software [18]. Not all data generated by ship operation need to be stored. Some important operation parameters need to be stored on the ship for more than half a year, and some non-important historical data should be deleted regularly to reserve enough server storage space.

In this case, the onboard server will periodically generate a large number of files. Before shoreside transmission, these data need to be compressed by a certain algorithm to reduce the number of data transmissions.

2.2. Data Processing

2.2.1. Data Preprocessing

When the ship is in operation, ship managers and engineers need to identify and analyze a large quantity of real-time information on board. However, data obtained from the MSAE, ship navigation, and environment contain errors caused by measurement uncertainty, manual recording problem, transmission, storage process error, and so forth. Abnormal data can easily lead to misjudgment of MSAE health conditions, leading to wrong decision-making and catastrophic accidents. Therefore, it is necessary to preprocess the ship's data. There are generally three preprocessing methods, as shown in Figure 2, data imputation, outlier detection, and redundant data deletion.

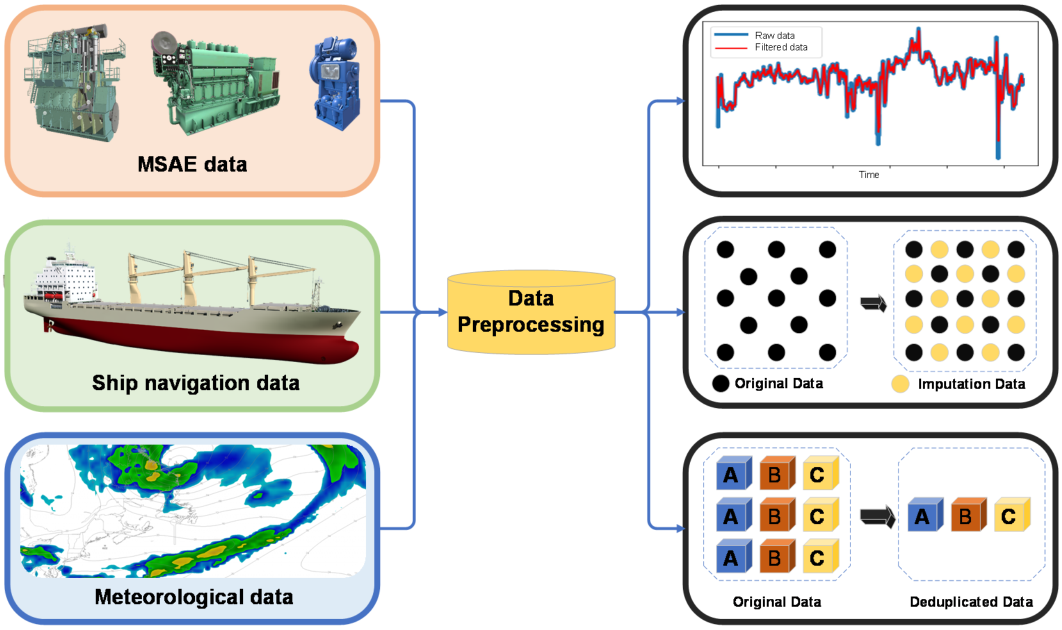


Figure 2. Data preprocessing diagram.

(1) Data imputation

Affected by various uncertainties, datasets from MSAE tend to contain a large amount of missing data [19,20]. The lack of data will lead to the deviation of diagnosis and prediction results, which will affect the decision-making of condition-based maintenance (CBM). Therefore, the imputation method is vital for increasing the quality of the original dataset and improving the decision-making for intelligent O&M.

Cheliotis et al. developed a new mixed imputation method to improve data quality [21]. The mixed-method is applied in the primary engine data set from a chemical vessel, and the results show that the average errors are smaller than the original algorithm. By correcting the sensor data from the HCM of MSAE, this mixed imputation algorithm tremendously improves the quality of the original data set. It relieved the conflict that the increasingly popular data-driven methods need complete data set for feature learning in the MSAE. Other imputation methods were applied to wind turbines [22] and cluster monitoring [23]. The effects of different missing data imputation methods were compared using cargo ships' sensor data [24];

(2) Outliers detection

Outliers in the data greatly impact the judgment of health conditions, so they need to be filtered out in advance during analysis. Jeon et al. presented a data gap analysis method that enables real-time detection of exception data in ships and marine data [25]. The method first detected original data after a series of data pretreatment and then sequentially detected the abnormal data in a relative error interval based on the predicted data obtained from the ship's performance element learning model. Wang et al. employed an abnormal detection scheme that can be used directly in process monitoring or process control. Compared with the traditional detection method, the assumption of the program is less, and it is more suitable for the modern industrial process [26]. Li et al. proposed a data cleaning and monitoring algorithm that can screen the abnormal data caused by natural factors and human factors [27]. Huyghues-Beaufond et al. presented a hybrid frame for detecting and removing extensive abnormal data [28]. The stacked auto-encoder method is widely used to monitor the contamination of abnormal values. The stacked auto-encoder has a powerful feature of functional extraction, which greatly retains the original information of the data [29]. The proposed method has superiority by comparing experiments with traditional abnormal value detection algorithms;

(3) Redundant data deletion

The redundant data on the ship mainly includes two parts. One is that in the process of data acquisition and transmission, some duplicate data will be generated due to the influence of sensors, transmission networks, and other influencing factors. The other is that some data acquisition cycles are short, and the data does not change in a short time. Redundant data will increase the amount of system calculation and affect the effect of model analysis.

Data preprocessing is a process to improve data quality and reduce noise. There are many sensors on the ship. The collected data has high dimensions and contains nonlinear data, which is very complex. At present, there is no general data preprocessing method suitable for all working conditions. Nowadays, most of the research methods are offline processing. More effective and stable ship real-time data processing methods are needed in the future, such as automatic data imputation and cleaning.

2.2.2. Feature Processing

Feature processing is a program to find out the useful features for classification and recognition from many features. This process also could compress the dimension of feature space, that is, to obtain a group of "few but fine" classification features with low classification error probability. At present, the feature processing methods in the application field of ships mainly include feature selection and feature extraction. The multi-dimensional data collected from ship complex equipment or systems need to be processed with these methods to obtain main operation characteristics, as shown in the blue block diagram in Figure 3.

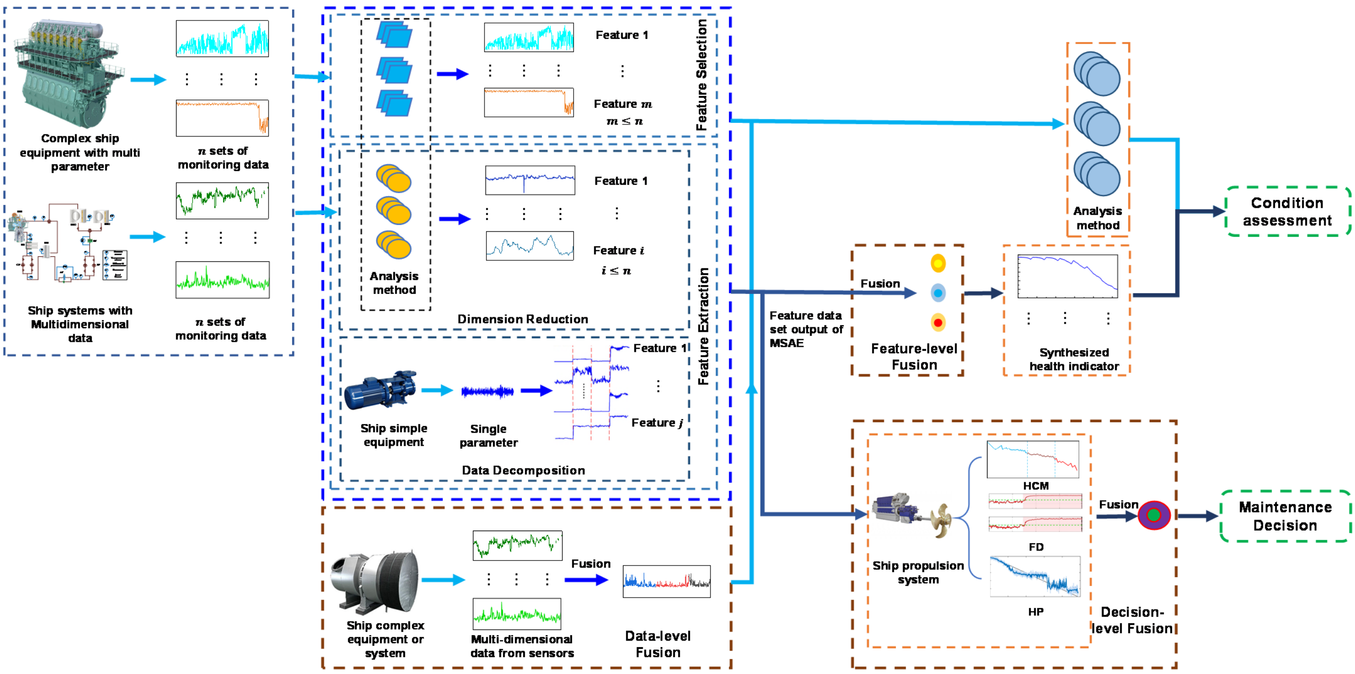


Figure 3. Feature selection and feature fusion structure.

(1) Feature selection

Feature selection is the process of selecting the relevant features of the data set from the original feature space according to a particular evaluation criterion. The selected feature data are a subset of the original data set, and it is an inclusive relationship [30]. A suitable method must be selected to analyze the original data to adapt to different algorithms' analysis and processing needs. Boullosa-Falces et al. and Ellefsen et al. employed the Pearson correlation analysis method to filter and analyze the data to obtain the optimal subset of equipment failure characteristics and reduced the impact of extreme data on the analysis results [31,32]. Tu et al. applied the Max-Relevance and Min-Redundancy method to process and analyze the data characteristics according to the correlation and redundancy [33]. To reduce the negative impact of irrelevant and redundant features between marine equipment status data on the analysis process, Wei et al. used K-means Clustering to select clustering features of ship equipment fault history data, which provides an effective tool for equipment failure analysis [34]. K-means clustering is a simple feature extraction method, which use a "central object" (gravitational center) obtained by the mean of each cluster center object. To improve the convergence speed of K-means in large-scale ship data, Shi et al. and Yan et al. proposed objective function and feature weighting to optimize it and apply the Fuzzy C-means clustering algorithm to process ship data [35,36]. Gaussian mixture model (GMM) algorithm, frequency sequence subtraction (FSS), and other methods were also applied to the selecting of features [9,37]. These feature selection methods can obtain the feature data set, remove the redundant data while retaining the characteristics of original MSAE data, and simplify the complexity of problem analysis;

(2) Feature extraction

Feature extraction is to transform the original feature space in a certain way through a particular method to obtain new features. The different feature extraction methods of the transformation result can be roughly divided into two categories: dimensionality reduction and decomposition extraction [38]. Haddad and Strangas used linear discriminant analysis to extract fault features and reduce the dimensionality of the main fault features to improve the accuracy and efficiency of fault recognition [39]. Zhou et al. presented principal component analysis (PCA) to analyze various oil parameters to reduce dimensionality, effectively realizing the state detection of marine steam turbines [40]. Yang et al. adapted ensemble empirical mode decomposition partly to decompose and extract the statistical ship propulsion shafting features of intrinsic mode functions and obtain a suitable fault feature vector set for corresponding analysis and diagnosis [41]. This is the type of data decomposition method. To improve the data analysis ability of the feature extraction method, some researchers applied the kernel function to optimize the extraction method and obtained comprehensive algorithms such as kernel independent component analysis (KICA) and kernel principal component analysis (KPCA) [42,43].

These feature extraction methods can effectively solve the dimension disaster caused by high-dimensional data and reduce the impact of data noise on the analysis results. However, when analyzing the MSAE data affected by many factors, the combined methods have greater advantages. Li et.al found that it could not meet the needs of fault diagnosis using the Fourier transform method to analyze the instantaneous angular velocity of marine diesel engines affected by multiple excitations. The combined method of EMD and KICA could be used to extract the feature, which effectively improves the efficiency and accuracy of main engine fault diagnosis [44]. The combination of multiple methods performs better in obtaining the data characteristics of MSAE and has advantages in condition monitoring.

2.2.3. Data Fusion

Due to the complex characteristics of ship machinery, a single set of data cannot fully express the overall operating condition. For example, the ship's navigation status is affected by fuel conditions, equipment working status, navigation area, weather conditions, and ship fouling [45]. Data fusion is the use of a certain algorithm to fuse multiple pieces of information from a single sensor or information provided by different types of sensors into a new and more expressive evaluation criterion. According to the characteristics of ship data, the fusion method can be roughly divided into three categories, namely data-level, feature-level, and decision-level, as shown in Figure 3.

The data-level fusion operation object is usually the measured data. Hou et al. applied support vector machines (SVM) and various evaluation functions to analyze the data and realize the ship's propulsion system's fault detection and health management [46]. Jiang et al. used the BP neural network method to realize the fault diagnosis of the turbocharger [47].

The feature-level fusion was oriented to feature fusion after the selection of monitoring objects. Jiang et al. applied the wavelet neural network to analyze the characteristic data extracted by Fourier and other methods and integrated the characteristic data of various equipment states, which further improves the accuracy of the actual fault state diagnosis of the ship [48]. For different types of ship monitoring data such as temperature, pressure, Wang et al. apply the normalization method to reduce the amplitude difference between the data, then combined PCA and BP neural networks to identify diesel engine failure modes [49].

The decision-level fusion is the fusion of data-oriented diagnosis and analysis results. Xu et al. proposed ER rules to integrate different fault diagnosis models of ship main engines, further established the primary engine wear fault diagnosis model, and improved the robustness and fault tolerance [50]. To ensure the navigation safety onboard, ship propulsion system needs to complete the state monitoring of the main engine, gearbox, shafting, and propeller. The main engine and gearbox are prone to failure and FD is necessary. The life of the main engine directly affects the ship's health management and needs failure prognostics. The decision fusion of the monitoring, diagnosis, and prediction results of the whole system is helpful to obtain specific O&M decisions.

The data of the ship mechanical system come from different kinds of sensors with huge intensity differences, such as marine diesel engine exhaust gas temperature (More than 300 °C) and lubricating oil pressure (0.3 MPa). Before data fusion, we need to normalize the data by scaling or transforming features to the same range to ensure that each data will have an equal contribution. The data are rescaled from different ranges to a predetermined range, and the original data distribution can be retained or not. Many normalization methods have been utilized in the research areas such as maritime accident data normalization [51], ship mechanical equipment data normalization [52]. Various types of data have different amounts of information, so the weight problem needs to be considered in the normalization process. The variable sorting for normalization was utilized to solve this problem in recent years in which considered the random consensus strategy to estimate the weights before implementing normalizations [53]." A novel Feature Wise Normalization approach was employed for the effective normalization of data which a unified solution is presented to address the shortcomings of traditional data normalization [54]. The general solution was formed based on a normalization unit established by various methods. This method could also be applied to marine field.

The current feature processing methods are mainly aimed at static data, and there are few applications for dynamic data processing. Most methods use high efficiency as the main evaluation criterion, and the applicability and safety of the methods need to be improved. Due to the harsh and complex working environment of MSAE, the diversity, dynamics, and high-latitude information monitored by sensors will be the main challenges for feature processing in the future.

2.3. Condition Monitoring

The condition monitoring system of MSAE uses various measurement and monitoring methods to record and display the operation condition, alarm the abnormal status, provide data and information for the fault detection, and deal with the upcoming and existing faults to achieve the purpose of automatic control. Condition monitoring technology is a very mature technology that is mainly used to distinguish between normal and abnormal states or discover potential and valuable information [55]. The traditional condition monitoring method is based on parameters alarm or manual identification, and the decisions are made when the corresponding parameters exceed their limits or threshold [56,57].

2.3.1. Categories of Condition Monitoring

There are many categories of condition monitoring such as online and offline, local and remote, data and video, equipment-level, and system-level. The condition monitoring of some special equipment, such as marine diesel engines, can be divided into conventional sensor monitoring and oil monitoring.

(1) Equipment-level condition monitoring

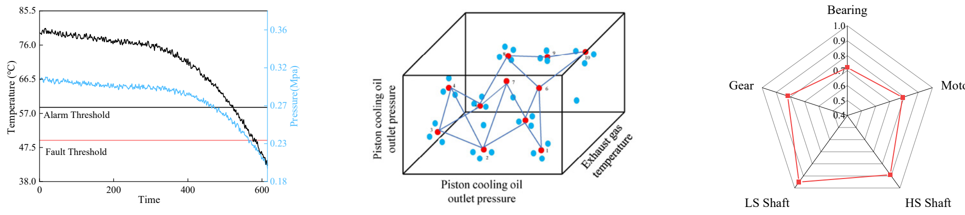
The actual state monitoring methods often integrate a variety of monitoring methods. Chandroth et al. proposed a method combining vibration data and performance data (cylinder pressures) to realize diesel engine condition monitoring [58]. Watzenig et al. performed the condition monitoring by constructing the thermodynamic model of the main and auxiliary diesel engines [59]. To further enhance the oil monitoring technology into marine field application, Yan et al. proposed a new online condition monitoring and remote FD system for marine diesel engines. The new system consisted of three parts, such as online signal acquisition, remote feature extraction, and fault diagnosis in the laboratory center [60]. To further improve the performance of monitoring and diagnostic, some researchers have made many contributions to the intelligent condition monitoring of MSAE. Yiannis et al. presented a novel approach for clustering data containing measurements of physical parameters for a marine diesel engine cylinder. This model monitored the condition of the main engine by clustering parameter measurements under normal conditions [61]. Asuquo et al. illustrated a fuzzy modeling approach utilizing IF-THEN rules and demonstrations of its usefulness [62];

(2) System-level condition monitoring

Different from single equipment condition monitoring, the system here can be large equipment on board, such as marine diesel engine and marine generator, or a combined system, such as the ship propulsion system, which can be further extended to the engine room monitoring system. At present, ship system-level condition monitoring mainly focuses on the diesel engine, propulsion system, cooling system, lubrication system, fuel system, and so forth. Lazakis et al. presented a novel methodology for system-level engine performance monitoring, which utilizes noon-report data with minimal data assumptions [20]. Condition monitoring was applied to the marine gas turbine propulsion system, and the real-time monitoring of system condition was realized [63]. Except for the proposed condition monitoring for the marine systems, ship AMS were implemented on modern vessels to support the efficient O&M [64]. A modular solution example of such a system is SeaPerformer which has been successfully implemented on a large number of merchant ships;

(3) Visualization tools for condition monitoring

There are many ways to express the results of condition monitoring, which can be roughly divided into curves or form (Figure 4a) or graphs (Figure 4b), and so forth. Yan et al. judged the severity of engine fault according to the diesel engine images using the online ferrographic sensor [60]. Yiannis et al. used self-organization mapping (SOM) topology graphs and tables to show the clustering of critical performance parameter data of engine cylinders to provide helpful data insight [61]. These curves or images can more simply and intuitively describe the health state of the diesel engine. However, it is usually only applicable to the case with a single parameter or few parameters. When monitoring the status of a multi-parameter system, the multi-parameter description method needs to be adopted. the radar chart method is usually used to describe the changes of system function [65], as shown in Figure 4c.



(**a**) (**b**) (**c**)

Figure 4. Visualization tools for condition monitoring: (**a**) Ship lubricating oil temperature, (**b**) The SOM graph of marine diesel engine cylinders, and (**c**) Radar chart of ship shafting.

2.3.2. Monitoring System for Ship Application

Among the existing condition monitoring system used onboard, Kongsberg, Transas, and Siemens occupy absolute advantages. According to the development process of monitoring technology, the marine condition monitoring system has experienced four stages: conventional instrument monitoring, centralized system, distributed system, and Fieldbus distributed system [66–68]. The typical feature of a centralized monitoring system (Direct digital control system) is to use the computer with a strong function to centrally monitor and control the power devices and systems in the engine room. The typical representative used on-board is the data chief-III system of Norcontrol company. The distributed monitoring system (distributed Multi-level microcomputer monitoring system) is a centralized and decentralized system composed of a microcomputer, digital regulator, programmable controller, and other units. Its typical representatives include the data chief 1000 system of Norcontrol and the SimOS ima32c system of Siemens. Fieldbus distributed system (Fully distributed monitoring system) uses Fieldbus as the internal control network of each subsystem and realizes the configuration of the control system at the field level. At present, the representative products of such systems include the chief data C20 developed by Norcontrol company.

Recent literature shows that CBM is an advanced maintenance strategy in many industrial fields, as well as in the maritime field [20,69]. Through the real-time monitoring of the MSAE, a large number of condition monitoring processing can be transformed into CBM to avoid the occurrence of severe faults and reduce the risk of casualties and maintenance costs.

2.4. Epilog

Condition monitoring could improve the reliability of MSAE and reduce the failure rate to improve the system's overall safety level, reduce the risk of life and property loss, and minimize the maintenance cost. Although many research achievements have been made on the related problems of ship condition monitoring, there are also many problems to be solved as soon as possible. For example, obtaining more comprehensive MSAE condition information, strengthening communication between equipment and systems, and intelligent condition assessment needs to be further improved.

3. Fault Diagnosis

The main function of FD is to detect, separate, and identify the faults in MSAE. Meanwhile, judge whether the fault occurs, determine the location and type and diagnose fault size and time. FD exhibits an essential role in demonstrating the relationship between the acquisition data and the health condition, which has got wide attention in MSAE health management, especially for ship O&M. Based on the way or extent they use a priori knowledge, FD methods could be classified into four categories, such as physical model-based method, knowledge-based method, data-driven method, and hybrid method.

3.1. FD Methods

3.1.1. Physics Model-Based Method

Physics model-based methods construct working processes of MSAE through building mathematical models based on the failure mechanisms. The core of analytical model-based technologies is the mathematical descriptions (modeling), and model analysis of process dynamics and main characteristics [70,71]. The model-based FD implementation process includes two parts: (I) Generating residual signal, the difference between model estimate values and measurements parameters; (II) Analyzing and estimating the residuals and making decisions.

Typical methods based on physical models for FD are bond graphs [72–74], parity space [75], parameter estimation [76] and state observers [77–79]. Those residuals are evaluated to realize the identification of abnormal conditions in the monitoring process. These methods compare the available measured values with the prior information, and the differences (residuals) between the measured variables and estimated values are used as the fault indicators.

Many model-based FD methods have been developed and applied to mechanical systems for fault identification. However, owing to the complexity of MSAE, there are many problems for building an accurate mathematical model to maintain robustness and fault sensitivity. Therefore, the model-based FD system has some restrictions in the practical application of marine engineering.

3.1.2. Knowledge-Based Method

Knowledge-based FD methods are considered approaches that could utilize the expert-level diagnosis knowledge to solve the identification of fault state instead of manual judgment, as shown in Figure 5. Those methods are based on the qualitative model of prior knowledge, and then the FD process is realized by running a mature search algorithm. The core of the knowledge-based FD system is an export control system composed of an expert knowledge base, a dynamic database, various inference engines, the user interface, and an explanation system. More and more attention has been paid to expert system-based FD technology in dealing with the complex process.

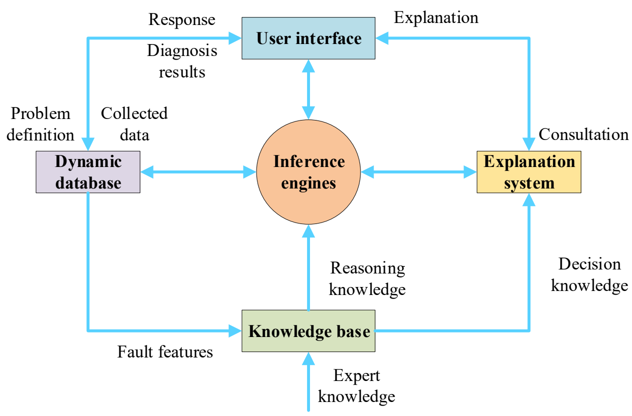


Figure 5. Knowledge-based FD models.

Rule-based reasoning, fuzzy logic-based reasoning, neural network-based reasoning, and case-based reasoning these four different classifications are used to distinguish knowledge-based diagnosis models according to different inference engines [80].

(1) The rule-based reasoning is employed to complete diagnosis knowledge and then uses the predetermined rules to realize decision-making. The rule-based reasoning was achieved better diagnosis performance for FD of marine diesel engines [81], centrifugal pumps [82], hydraulic systems [83], and bearings [84]. A rule-based reasoning model for ship power systems is established based on the classification society's operational

mode requirements and regulations. The main engines, diesel-electric engines, and energy storage systems were considered [85]. Rule-based reasoning could build a nonlinear mapping relationship between feature and health condition, but with the increase of MSAE complexity, the number of rules required increases greatly so that the reasoning efficiency will decrease significantly;

(2) Fuzzy set theory is introduced into inference engine to realize fuzzy logic-based reasoning. Through this method, imprecise non-numerical information description can be realized. The fuzzy logic-based reasoning method was first applied to power systems [86]. The application of Fuzzy logic-based reasoning for FD on board mainly includes scooter engines [87], bearings [88,89], gear systems [90]. The performance of the method is affected by the difficulty of obtaining a fuzzy dataset, which will reduce the fault identification accuracy;

(3) The neural network-based reasoning makes full use of the neural networks' learning, association, and memory ability to realize the intelligent reasoning of diagnostic knowledge. The application of the method mainly includes internal combustion engines [91], bearing [92]. Method implementation depends on sufficient fault data to realize model training, which is difficult to obtain in MSAE. In addition, the neural network adopts the black box principle, and the accurate mapping between some physical processes and diagnostic knowledge is not easy to realize;

(4) Case-based reasoning uses similar existing cases to solve the technical problem. At present, this method is widely used in ship collision avoidance and ship design, and the application of MSAE fault diagnosis has not been found.

The knowledge-based fault diagnosis model uses the knowledge of experts to construct an inference engine to realize fault pattern recognition. The model is highly dependent on expert knowledge, and the accuracy of expert knowledge directly affects the diagnosis results. Moreover, the model has no self-learning ability and can only solve the existing problems.

3.1.3. Data Driven-Based Method

The data-driven FD method of MSAE originates from the condition monitoring technology and has attracted the attention of more and more engineers and researchers. The implementation procedure of data-driven methods simply involves two steps: a training model based on historical data and an online FD based on real-time data. In this section, the data-driven FD methods for MSAE will be summarized in detail.

Data-driven FD methods mainly include signal processing, multivariate statistical analysis, and machine learning. These methods adaptively learn the diagnosis knowledge and automatically establish the relationship between the measurement parameters and the health condition of MSAE instead of expert experience and knowledge.

(1) Signal processing methods

Some of the collected and processed signals carry the fault information, which is presented as characteristics. Fault diagnosis can be realized by generating fault symptoms with appropriate signal processing methods [93]. Typical symptoms include time-domain features such as amplitude, arithmetic or square mean, limit value, partial derivative, the statistical moment of amplitude distribution or envelope, or frequency-domain features such as spectral power density, spectral line, and cepstrum analysis. Typically, the existing signal analysis-based FD methods for MSAE mainly include three categories [94], such as time-domain methods, frequency-domain methods, and time-frequency-domain methods. Xi et al. proposed an automatic vibration-source extraction and feature visualization method fault detection of marine diesel engines where a time-frequency reference signal constructed by Stockwell transform (ST) method. Then, the t-distributed stochastic neighbor embedding (t-SNE) is used to extract fault features and realize visualization to intelligently identify diesel engine faults [42]. The ST method can be indicated as:

$$y(\tau, f) = \int_{-\infty}^{\infty} x(t)|f|e^{-\pi(\tau-t)^2 f^2} e^{-j2\pi f t} dt, \tag{1}$$

where $x(t)$ is the sensor signal, τ and f are the time and frequency terms, and the $|f|e^{-\pi(\tau-t)^2 f^2}$ is a Gaussian window. When the integration result of the Gaussian window is equal to 1 in the integration operation, we can obtain:

$$\begin{aligned} Y &= \int_{-\infty}^{\infty} y(\tau, f)d\tau = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x(t)\omega(\tau-t, f)e^{-j2\pi ft}dtd\tau \\ &= \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}\left\{\int_{-\infty}^{\infty}\omega(\tau-t, f)d\tau\right\}dt = X(f) \end{aligned} \tag{2}$$

where $X(f)$ is the Fourier transform of $x(t)$. The original signal $x(t)$ can be recovered by performing inverse Fourier transform on Y based on Equation (2). Then, t-SNE is used to select the most obvious fault characteristics. This method learns a map F by measuring the pairwise similarity of the elements in parameter set D, and projects D into a low dimensional (usually 2 or 3) embedding $E = [e_1, e_2, \cdots e_l]^T$, as shown in Equation (3).

$$\begin{cases} p_{j|i} = \dfrac{\exp\left(-F\left(d_i, d_j\right)^2/2\sigma_i^2\right)}{\sum_{k\neq i}\exp\left(-F(d_i, d_k)^2/2\sigma_i^2\right)}, and\ p_{j|i} = 0 \\ p_{ij} = \left(p_{i|j} + p_{j|i}\right)/2l \end{cases}, \tag{3}$$

where p_{ij} and $p_{j|i}$ are the joint and the conditional probability between d_i and d_j, σ_i is the bandwidth of the Gaussian kernels. The pairwise similarity of the elements in E is expressed as

$$\widetilde{p}_{ij} = \frac{\left(1 + \|e_i - e_j\|^2\right)^{-1}}{\sum_{k\neq h}\left(1 + \|e_k - e_h\|^2\right)^{-1}}, and\ \widetilde{p}_{ii} = 0\,, \tag{4}$$

where $\widetilde{p}_{ij}$ is the joint probability between e_i and e_j.Lastly, the location of embedding element e_i will be determined by optimizing the Kullback-Leibler divergence between the joint distributions p_{ij} and $\widetilde{p}_{ij}$. The implementation process is shown in Figure 6.

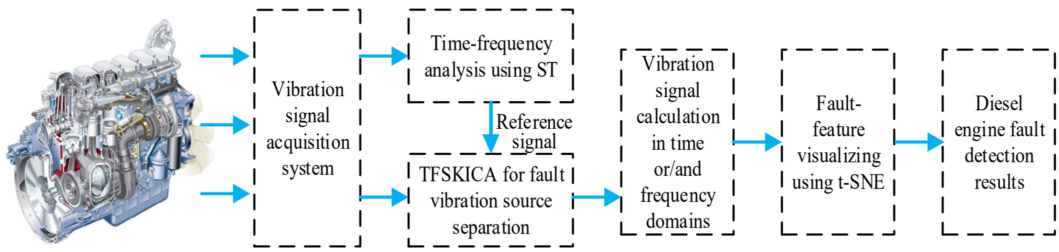


Figure 6. FD of diesel engine based on signal processing method.

The signal processing methods could cost a lot of human and financial resources since they require expert experience, extensive computational and storage resources, and robustness of the selected features, limiting their practical applications in PHM.

(2) Multivariate statistical analysis

Typically, the applications of multivariate statistical analysis methods in MSAE mainly include PCA, independent component analysis (ICA).

- PCA

PCA can reduce the dimension of the dataset and retain the essential information of original measurement parameters to the greatest extent. This is very important for complex MSAE with many correlated variables.

For a given data matrix with N observation samples and M variables, PCA identifies the sub-space with the largest variance in the M-dimensional variable space and linearly transforms the original variables into the principal components (PCs). Select the first A components from PCs and capture most of the percentage of variance. Its model expressed as

$$\boldsymbol{X} = \boldsymbol{T}_A \cdot \boldsymbol{P}'_A + \boldsymbol{E}\,, \tag{5}$$

where $\boldsymbol{T}_A$ is the score matrix of size $N \times A$, $\boldsymbol{P}_A$ is the loading matrix of size $M \times A$, and $\boldsymbol{E}$ is the residual matrix of size $N \times M$, corresponding to the variance not captured by the PCA model.

The scores for a new observation, $\boldsymbol{t}_{new}$, are computed by projecting the row vector corresponding to that observation, $\boldsymbol{x}_{new}$, onto the model subspace:

$$\boldsymbol{t}_{new} = \boldsymbol{x}_{new} \cdot \boldsymbol{P}_A\,. \tag{6}$$

Once the scores have been computed, the residuals, $\boldsymbol{e}_{new}$, are calculated:

$$\boldsymbol{e}_{new} = \boldsymbol{x}_{new} - \boldsymbol{t}_{new} \cdot \boldsymbol{P}'_A\,. \tag{7}$$

Zhan et al. presented the use of a multi-class SVM for the FD of marine diesel engine cylinder covers, based on vibration analysis and PCA [95]. PCA as a foremost step of integration fault detection method of marine current turbines was proposed by Xie et al. [37]. The PCA-based approach was used for building on-board sensor classifiers for water contaminant detection [96].

- ICA

ICA is capable of separating independent sources contained in the observations and, therefore, suitable for MSAE with multiply sensors data.

For a given sample set $\boldsymbol{x} \in R^d$ can be expressed as linear combination of m unknown independent components $\boldsymbol{s} = [s_1, s_2, \cdots, s_m] \in R^m$, that is,

$$\boldsymbol{x} = \boldsymbol{A}\boldsymbol{s}, \tag{8}$$

where $\boldsymbol{A} \in R^{d \times m}$ is the mixing matrix.

ICA tries to estimate $\boldsymbol{A}$ and $\boldsymbol{s}$ only from the known $\boldsymbol{x}$. Therefore, it is necessary to find a de-mixing matrix $\boldsymbol{W}$ which is given as:

$$\hat{\boldsymbol{s}} = \boldsymbol{W}\boldsymbol{x}, \tag{9}$$

such that the reconstructed vector $\hat{\boldsymbol{s}}$ becomes as independent as possible. For convenience, we assume $d = m$, and $E(\boldsymbol{s}\boldsymbol{s}^{\mathrm{T}}) = \boldsymbol{I}$. The whitening transformation is expressed as

$$\boldsymbol{z}\text{=}\boldsymbol{Q}\boldsymbol{x}\text{=}\boldsymbol{Q}\boldsymbol{A}\boldsymbol{s}\text{=}\boldsymbol{B}\boldsymbol{s}, \tag{10}$$

where whitening matrix $\boldsymbol{Q} = \Lambda^{-1/2}\boldsymbol{U}^{\mathrm{T}}\boldsymbol{x}$, $\boldsymbol{B}$ is an orthogonal matrix. The relationship between $\boldsymbol{W}$ and $\boldsymbol{B}$ is as

$$\boldsymbol{W} = \boldsymbol{B}^{\mathrm{T}}\boldsymbol{Q}. \tag{11}$$

Hence, Equation (9) can be rewritten as

$$\hat{\boldsymbol{s}} = \boldsymbol{W}\boldsymbol{x} = \boldsymbol{B}^{\mathrm{T}}\boldsymbol{z} = \boldsymbol{B}^{\mathrm{T}}\boldsymbol{Q}\boldsymbol{x} = \boldsymbol{B}^{\mathrm{T}}\Lambda^{-1/2}\boldsymbol{U}^{\mathrm{T}}\boldsymbol{x}. \tag{12}$$

According to Equation (11), the ICA problem can be reduced to find an orthogonal matrix $\boldsymbol{B}$.

ICA-based scheme decomposes these acoustic signals for diesel engine fuel injection FD [97]. Li et al. applied a new ICA to identify the characteristic of the engine vibration signals to improve the fault detection performance for marine diesel engines [98]. Jing et al. proposed the ICA and SVM for diesel engine condition monitoring and FD [99].

(3) Traditional Machine learning

In recent years, these traditional machine learning theories, including ANN and SVM, are applied to MSAE fault diagnosis.

- ANN-based FD model

ANN-based FD model has strong self-learning ability. It can obtain diagnosis knowledge from input data and realize fault pattern recognition.

Given the training dataset $\{\boldsymbol{x}_i, \boldsymbol{y}_i\}_{i=1}^{m}$ with m samples, where $\boldsymbol{x}_i \in R^d$ includes d features and $\boldsymbol{y}_i \in R^l$ includes l health states, the output of the h th hidden layer is expressed as

$$\left(\boldsymbol{x}_i^h\right)_j = \sigma^h\left(\sum_{i=1}^{n_{h-1}} \omega_j^h \cdot \boldsymbol{x}_i^{h-1} + b_j^h\right), j = 1, 2, \cdots, n_h, h = 1, 2, \cdots, H, \tag{13}$$

where $\left(\boldsymbol{x}_i^h\right)_j$ is the output of the j th neuron in the h th hidden layer, and $\boldsymbol{x}_i^0 = \boldsymbol{x}_i$, n_h is the number of neurons in the h th hidden layer, σ^h represents the activation function of the h th hidden layer, n_{h-1} is the number of neurons in the $(h-1)$ th hidden layer, ω_j^h is the weights between the neurons in the previous layer and the j th neuron in the h th hidden layer, and b_j^h is the bias of the h th hidden layer. The predicted output is

$$\left(\hat{\boldsymbol{y}}_i\right)_k = \sigma^{out}\left(\sum_{i=1}^{n_H} \omega_j^{out} \cdot \boldsymbol{x}_i^H + b_j^{out}\right), k = 1, 2, \cdots, l, \tag{14}$$

where $\left(\hat{\boldsymbol{y}}_i\right)_k$ is the predicted output of the k th neuron in the output layer, σ^{out} is the activation function of the output layer, ω_j^{out} and b_j^{out} are respectively the weights and bias of the output layer.

ANN is widely used in FD of the rotor system, hydraulic unit, bearing, and gearbox. Zhong et al. applied a hierarchical ANN model for the rotating machines, which decompose large pattern space into several subspaces [100]. This method could be used to diagnose a variety of faults. Yang et al. presented an FD model using the Kohonen neural network for the rotary machinery [101]. The probabilistic neural network was employed for efficiently FD of hydraulic units [102]. Barakat et al. applied the growing neural network to establish an FD model for bearings, which obtained a better diagnostic effect than traditional methods. Li et al. realize marine gearbox fault condition monitoring by using a neural network to analyze its vibration signal [103]. A feed-forward ANN for the condition monitoring of the air intake and fuel injection system of a medium-speed marine engine had been proposed [104]. Raptodimos et al. proposed an ANNs fusion SOM method for the HCM of a marine diesel engine [61].

Although many ANN methods have been successful in mechanical FD, this method also has disadvantages. One is that the complexity of the model increases significantly with the growth of input condition parameters. The increasing input data affect training efficiency and may lead to overfitting of the model. On the other hand, the ANN-based FD models are based on the black box principle and lack the relationship mapping of physical processes. Some results could not be reasonably explained.

- SVM-based FD model

SVM is a supervised learning method with the input vectors $\boldsymbol{x}_i \in R^d (i = 1, 2, \cdots, n)$ and the corresponding labels $\boldsymbol{y}_i \in \{-1, +1\}$. There exists a separating hyperplane and expresed as

$$\delta \cdot \boldsymbol{x} + b = 0, \tag{15}$$

where $\delta \in R^n$ is a normal vector, the b is a scale, and $\frac{|b|}{\|\delta\|}$ represents the perpendicular distance from the separating hyperplane to the origin. Two parallel hyperplanes can be represented as

$$y_i(\delta \cdot \boldsymbol{x}_i + b) \geq 1. \tag{16}$$

SVM tries to maximize the margin between two classes, where the margin width between the two parallel hyperplanes equals to $\frac{2}{\|\delta\|}$. Therefore, the optimization objective of the linear SVM is

$$\begin{array}{l} Min\ \frac{1}{2}\|\delta\|^2 \\ s.t.\ y_i(\delta \cdot \boldsymbol{x}_i + b) \geq 1 \end{array} \tag{17}$$

SVM is a widely used machine learning method in pattern recognition, especially for FD of centrifugal pumps [105], rolling bearing [106], gearbox [107], wind turbine [108], marine diesel engine [109]. Zhan et al. used SVM to realize fault diagnosis of marine main engine cylinder cover [95]. One-class support vector machine (OC-SVM) was firstly used to divide the input data of marine turbocharger system into two parts, normal and abnormal, and only the fault data are used to identify specific fault types [110]. By this means, automatic fault diagnosis of the system was realized.

Compared with the ANN method, SVM-based FD models have better model interpretability performance and could easily realize the optimal global solution and obtain high diagnosis accuracy [80]. The SVM method also has disadvantages. Firstly, the method is mainly suitable for small sample data. With the improvement of ship intelligence, the method will not be suitable for big data. Furthermore, the performance of the diagnostic model is affected by kernel parameters, and its selection has a great impact on the accuracy of the model. Finally, complicated architectures are needed when facing the multi-class classification problem, and a single SVM model could not meet the requirements.

The performance of data-driven FD approaches mainly relies on the quality and quantity of state parameters. Insufficient data has become the main factor limiting the wide application in MSAE. Therefore, the data-driven FD method is applied to some equipment and components with relatively sufficient data. Whenever the historical data could not contain complete status information, approaches based on physical model-based or knowledge-based methods come into play.

3.1.4. Hybrid Approaches

A single FD method has its advantages and disadvantages and has different applications. There is no general FD method suitable for all the working conditions or scenarios. Therefore, the hybrid model takes into account the advantages of each model, realizes the complementarity between models, and then improves the diagnosis accuracy and decision rationality.

The fusion of more than one FD method into a hybrid model may be realized in many ways. Physical model and data-driven approach are combined for rotating machinery FD and HP [111]. Since it is complicated to obtain the complete degradation data from the operating systems and equipment, the physical model simulation method can be used to simulate the actual operation condition and generate synthetic data. The combination of data simulation, through physical modeling, with both supervised and unsupervised Machine Learning methods has been examined with application to system decay in naval vessels [7,112]. An innovative hybrid FD method based on manifold learning and the isolation forest was established to diagnosis the condition of marine diesel engines [113]. ICA, short-time Fourier transform, PCA, and Fuzzy neural network (FNN) are fused as a new development method to realize marine diesel engines condition monitoring and FD [114].

3.2. Current New Fault Diagnosis Algorithm

With the rapid development of machine intelligence and sensing technology, modern intelligent ships have rapidly increased DIaK. Unfortunately, the FD methods based on traditional machine learning are unable to make accurate decisions under multiple and complex information scenarios and different working modes. Therefore, it is necessary to present some advanced intelligent FD methods. At present, the intelligent FD methods used by MSAE mainly include deep learning-based and transfer learning-based methods.

3.2.1. Intelligent FD Methods Using Deep Learning Theories

Deep learning, also known as deep neural networks (DNN), employs deep hierarchical architectures (sparse auto-encoder (SAE), deep belief networks (DBN), convolutional neural network (CNN)) with multiple neural layers to extracts the information features automatically, and further realize the mapping between learned features and output results. SAE is an unsupervised learning method. By constructing a self-encoder structure to obtain the transform output that can approximate the input signal, the model can obtain the internal characteristics of data without labels or a small number of labels after training, which can be used to study the sample missing or imbalance in fault diagnosis. DBN solves the global optimization problem of multilayer networks by layer by layer training. Reasonable initial values and weights are selected for the whole network structure, and then the optimal solution of the network can be obtained by fine-tuning the parameters. SAE was developed as a monitoring model to realize the FD of the air compressors [115]. DBN was applied to diagnose gearboxes and bearings [116]. The following will briefly introduce CNN and its process of realizing MSAE fault diagnosis.

The structure of CNN is divided into 2-dimensional and 1-dimensional diagnostic models. Because 1D CNN can directly process 1D signals such as vibration signals, it is widely used in fault diagnosis of rolling bearings, motors, hydraulic pumps, and other equipment. Ince et al. proposed a motor fault diagnosis system based on 1D CNN as shown in Figure 7, which fused the feature extraction and classification in the traditional fault detection methods into a single module [117]. The forward propagation from convolution layer $l-1$ to current neuron input layer l can be expressed as

$$x_k^l = b_k^l + \sum_{i=1}^{N_{l-1}} conv1D\left(w_{ik}^{l-1}, s_i^{l-1}\right) \tag{18}$$

where x_k^l is the input, b_k^l is a scalar bias of the k th neuron at the layer l, and s_i^{l-1} is the output of the i th neuron at the layer $l-1$, w_{ik}^{l-1} is the kernel. Use the input x_k^l to calculate the intermediate output y_k^l, which can be written as

$$y_k^l = f\left(x_k^l\right) \; and \; s_k^l = y_k^l \downarrow ss \tag{19}$$

where s_k^l is the output of the neuron and $\downarrow ss$ represents the down-sampling operation with the factor ss. This method is directly applicable to the real-time data for a single equipment like a marine motor, so there is no need for a separate feature extraction algorithm, which makes the system more efficient in speed and hardware. This method is also applicable to the FD of MSAE by directly extracting signals from the ship end database.

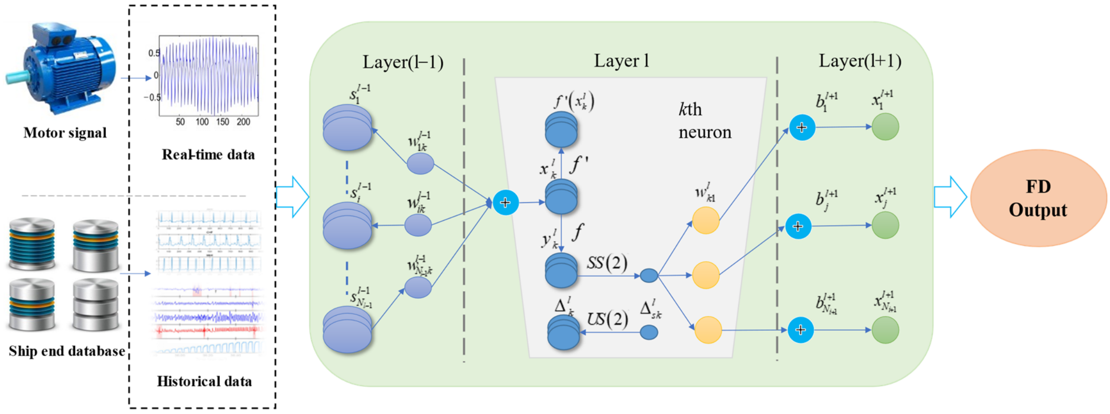


Figure 7. FD method of MSAE based on 1D CNN.

Diagnosis models based on the CNN method can directly capture the shift variant properties and learn features from measurement parameters from MSAE without preprocessing to obtain the corresponding characteristics. Furthermore, due to the shared weight method, the training data of the diagnostic model could be reduced, which is helpful to accelerate the convergence speed and prevent over-fitting. Like other deep learning methods, CNN also needs sufficient labeled samples to train the model to improve diagnostic efficiency.

3.2.2. Intelligent FD Methods Using Transfer Learning Theories

Sufficient labeled data are necessary for data-driven methods to train diagnosis models. However, in marine engineering scenarios, obtaining appropriate data and further labeling them will be hard to implement. Previous test results or relevant data of the same or similar MSAE can be used as diagnostic knowledge. For example, the diagnosis knowledge from manufacturer's test, such as bench test and sea trial, may help recognize the health condition. Transfer learning could use the diagnosis knowledge of existing systems and equipment to realize the diagnosis of new equipment [118]. Feature-based transfer learning approaches which could realize correcting serious across-domain discrepancy are widely used.

Transfer component analysis (TCA) is a typical feature-based approach and its optimization objective is

$$\min_{W} \operatorname{trace}\left(\boldsymbol{W}^{\mathrm{T}}\boldsymbol{KLKW}\right) + \mu \cdot \operatorname{trace}\left(\boldsymbol{W}^{\mathrm{T}}\boldsymbol{W}\right),\ \text{s.t. } \boldsymbol{W}^{\mathrm{T}}\boldsymbol{KHKW} = \boldsymbol{I}, \tag{20}$$

where $\boldsymbol{K} = [K_{i,j}] \in R^{(n_s+n_t)\times(n_s+n_t)}$ is the kernel matrix of the input cross-domain samples and $K_{i,j} = k(\boldsymbol{x}_i, \boldsymbol{x}_j)$, $\boldsymbol{W} = \boldsymbol{K}^{-1/2}\boldsymbol{W} \in R^{(n_s+n_t)\times m}$ maps the cross-domain samples from the space $R^{n_s+n_t}$ to the m-dimensional space R^m and $n_s + n_t > m$,μ is the tradeoff parameter, $\boldsymbol{H} = \boldsymbol{I}_{n_s+n_t} - 1/(n_s + n_t)11^{\mathrm{T}}$ is the centering matrix, and $\boldsymbol{L} = [L_{i,j}] \geq 0$ can be calculated as

$$L_{i,j} = \begin{cases} \frac{1}{n_s^2}, & \boldsymbol{x}_i, \boldsymbol{x}_j \in X^s \\ \frac{1}{n_t^2}, & \boldsymbol{x}_i, \boldsymbol{x}_j \in X^t \\ -\frac{1}{n_s n_t}, & \begin{cases} \boldsymbol{x}_i \in X^s, \boldsymbol{x}_j \in X^t \\ \boldsymbol{x}_i \in X^t, \boldsymbol{x}_j \in X^s \end{cases} \end{cases}. \tag{21}$$

The optimal feature mapping $\boldsymbol{W}^*$ obtained by solving Equation (20) can be further used to calculate the cross-domain features $\boldsymbol{W}^*\boldsymbol{K}$ subject to a similar distribution.

As described in Figure 8, such approaches could be classified into feature mapping, feature extraction, feature adaptive update, and fault identification.

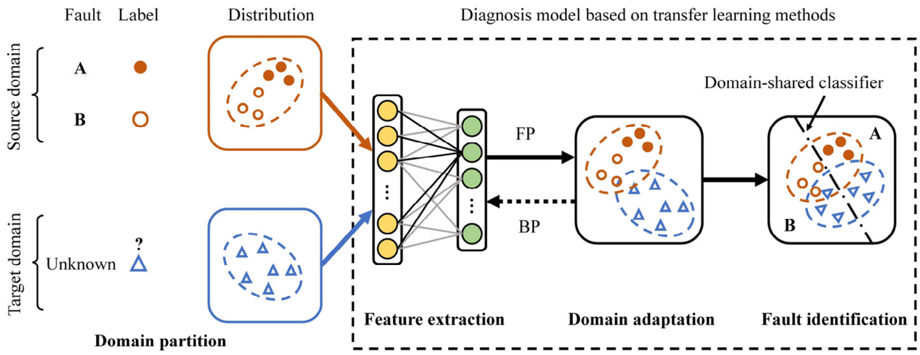


Figure 8. Step of feature-based transfer learning approaches [119].

The development of intelligent ship technologies promotes the sharing of data between different ships. The effective extraction, transfer, and application of knowledge in the later stage will become the critical research content of the ship intelligent O&M. FD model based on transfer learning, shown in Figure 9. The primary calculation process of the algorithm includes the construction of input data, empirical and depth feature extraction, feature transfer learning, fault pattern recognition.

(1) The input data

On the one hand, making full use of the test bench provided by various MSAE manufacturers, a large number of test data collected from the factory, ship mooring, and sea trial data, and the massive operation data, a state knowledge transfer learning model was established to reduce the distribution difference of working conditions and operating environment in the migration characteristic layer. The problems of non-convergence and low recognition accuracy caused by insufficient marking information in the existing MSAE state diagnosis model could be effectively solved. On the other hand, knowledge extraction, transferring, and adaptation are carried out for the status data of different ship service life, operation process information of different working conditions and environment, and data samples of different fault types, to promote the transferring and sharing of characteristic knowledge among monitoring data.

(2) Empirical and depth feature extraction

Taking the empirical feature and multi-scale depth feature as the input, the sensitive feature selection and identification ability of random forest are used to complete the identification of the operation state of MSAE [120]. The parameters of the empirical feature extraction model and ResNet network were adjusted using the back-propagation network and gradient optimization algorithm.

(3) Feature transfer learning

The transfer learning needs to go through the following process. The empirical and depth joint feature transfer learning model for multi-source sensing information is designed, and the multi-core function space combination structure is constructed. Then the joint features are mapped to high-dimensional space. Finally, the popular learning mapping network is designed to complete the low-dimensional re-projection of high-dimensional spatial features.

(4) Fault pattern recognition

The hybrid kernel functions and the structural parameters of the network are optimized by the iterative method, and then the model training is completed. Based on the deep transfer learning FD model, combined with the incremental learning method, the network parameters are optimized using the continuously collected sensor data to further improve state recognition accuracy.

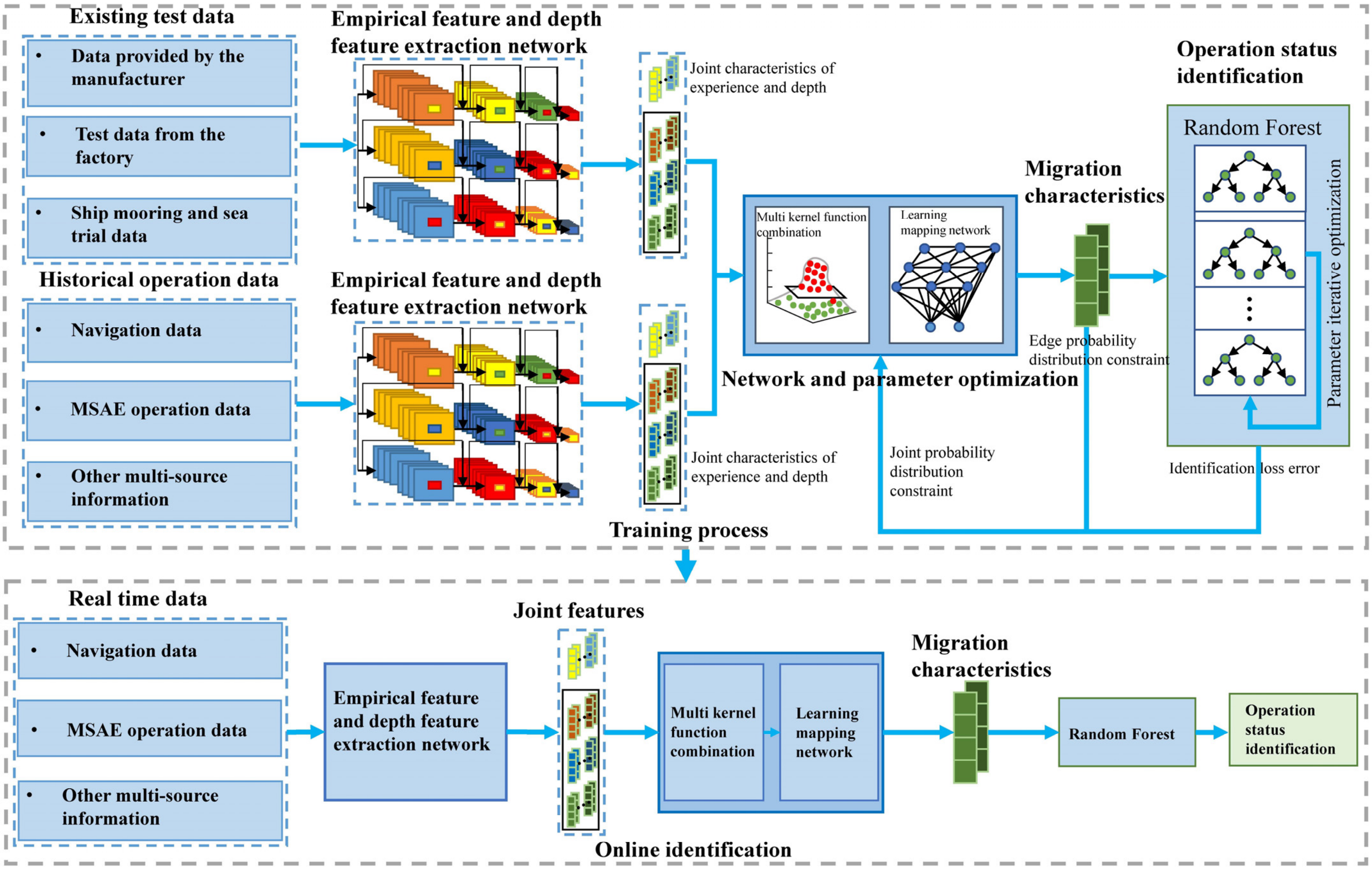


Figure 9. FD model of MSAE based on transfer learning.

Because of the above characteristics of transfer learning theories, it is essential to obtain sufficient labeled data, which relieves the limitations of traditional machine learning on FD model training. Accordingly, an intelligent FD model using this method could solve the problem from theory to marine engineering application.

3.3. Summary of Application

The main applications of FD methods in MSAE are shown in Table 3. At present, ship FD methods mainly focus on key equipment such as marine diesel engines and propulsion systems, and the research on auxiliary equipment and system is relatively few. In addition to independent equipment and system FD, some mature diagnosis systems, such as the Marine Performance Monitoring System of Norway KYMA Company, and the CoCoS Engine Diagnostic System of MAN as well as the DICARE of Caterpillar have been successively developed and applied in the shipping industry.

Table 3. Summary of application to MSAE fault diagnosis.

Methodologies		References	Marine Objects
Physics model-based method	Bond graph	(Tan et al., Huang et al., Pedersen and Pedersen, Huang et al., Huang et al.) [73,74,121–123]	Feedwater system Condenser Power system Diesel engine
	Parity space	(Benetazzo et al.) [124]	Dynamic positioning system
	Parameter estimation	(Wang et al., Nagy-Kiss et al., Torres et al. Zhang and Chen, Zhou, et al.) [76,125–128]	Raisers Current turbine Prolusion system
	Observers	(Chu et al., Cui et al., Lootsma et al., Qiao and Yang, Wang and Han, Zhou et al.) [78,129–133]	Underwater thruster Propulsion system Unmanned surface vehicle
Knowledge-based methods	Rule-based reasoning	(Xu et al., Hein et al., Roy, Coenen and Smeaton.) [81,85,134,135]	Power system Diesel engine
	Fuzzy logic-based reasoning	(Berredjem and Benidir, Ahmed and Gu, Shah and Wang, Qiao and Yang.) [88–90,136]	Boiler Prolusion system Bearing
	Neural network-based reasoning	(Wu et al.) [91]	Diesel engine
Data driven-based method	Signal processing	(Xi et al., Marichal et al., Zhan et al., Freeman et al., Dayong et al., Hu et al., Cui and Ma.) [42,137–142]	Diesel engine Separator Systems Current turbine Ship Antennas Rolling Bearing
	Multivariate statistical analysis	(Zhang et al., Wang et al., Peng et al., Zhong et al., Fabiani et al.) [41,43,143–146]	Diesel engine Ship fuel system AUV Thrusters Turbine generators
	Machine learning	(Zhan et al., Raptodimos and Lazakis, Xu et al., Pantelelis et al., Cheliotis et al., 2020; Karagiannidis and Themelis.) [50,61,95,147–149]	Diesel engine Turbocharger Ship systems
Hybrid approaches	Method fusion	(Jiang et al., 2021; Wang et al., Li et al., Xu et al., Sánchez-Herguedas et al., Qin et al., Zhou et al.) [40,48,50,113,114,150,151]	Diesel engine Propulsion shaft system
	Data and information fusion	(Xie et al., Li et al.) [37,114]	Current turbine

3.4. Epilog

This section reviews the FD methods on-board. The advantages and disadvantages of different diagnosis methods are analyzed, and their applications in the shipping field are summarized. Although the FD methods have achieved good application onboard, they still face many problems.

- Under normal conditions, some MSAEs are not allowed to run to failure as an unexpected failure could result in a breakdown of the ship, maritime traffic accidents, casualties, and environmental pollution. Consequently, failure data in various modes are difficult to be obtained in marine fields.

- Marine machinery, such as main engines, propulsion systems, always works under rough sea conditions. Some external uncertainties from the outside environment (wind, wave, and current) and internal environment (vibration, noise, and electromagnetic) are mixed into the measurement parameters, thus increasing the difficulty of fault pattern recognition.
- Working modes identification is important. The MSAEs work alternately in a variety of working modes. When the modes are different, the optimal value (baseline value) and limits (thresholds) of the same variable will be significantly different, which will increase the difficulty of fault identification.

4. Health Prognostics

As the main task of PHM, HP is a process of reasonably estimating the remaining life of mechanical equipment by using the degradation trend from HCM information. HP could make real-time health condition evaluation and accurate RUL prediction for the whole system and its auxiliary components in operation, so those marine engineers could make optimal maintenance decisions and ensure reliability and safety [152,153]. The HP framework of MSAE is mainly composed of three parts: HI construction, HS division, and RUL prediction. This chapter systematically reviews the literature of these three parts.

4.1. HI Construction

The effective prediction of RUL mainly depends on the explicit HI that fully reflects the dynamic performance degradation [154]. HI is a statistical or quantitative indicator that was used to display the health condition of MSAE. A suitable HI not only helps to promote data visualization but can also continuously characterize the health conditions of the monitored system throughout the life cycle, correctly reflect the degradation, and has an apparent monotonic trend [155]. Therefore, how to obtain explicit HI is an important problem.

For different devices, the expression forms and construction methods of HI are also different. Some equipment has the dominant characteristics of degradation, such as RMS and kurtosis of bearing, the discharge pressure of the pump, and so forth, which can be classified as a single HI type. The implicit assumption is that the degradation characteristics of the equipment could be described with a single sensor parameter so that the prediction method can be modeled with this signal. However, this simple assumption may not be valid in many complex equipment and system-level applications since a single feature often leads to unreliable prediction analysis [156,157]. When multiple signals can be collected, each signal contains some information about the health state of the system. Only modeling with a single parameter that can best characterize its degradation could not accurately predict the degradation process and wastes many monitoring data. Therefore, combining multiple available sensor signals to construct the synthesized HI to evaluate the degradation process is an accurate and effective method [158]. The following will summarize the research of single HI and synthesize HI, respectively.

4.1.1. Single HI

Where there is a complete degradation mechanism shown to be related to the equipment or the whole system, and its fault physics could be represented by a single sensor signal which reflects most characteristics of the potential degradation process, it is an easy and reliable method to use the single HI to characterize the health condition of MSAE [159]. Single HI could be statistical features directly extracted from the time series of monitoring data, such as root mean square (RMS), skewness, kurtosis, and so forth. [160].

RMS evaluates the overall condition of the equipment by tracking the progress of the fault and is not sensitive to early faults.

$$s_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2}. \tag{22}$$

Skewness represents the symmetry of the probability density function of the signals of a time series.

$$\gamma_{skewness} = \frac{N \cdot \sum_{i=1}^{N} (x_i - \overline{x})^3}{\left\{ \sqrt{\sum_{i=1}^{N} (x_i - \overline{x})^2} \right\}^3}. \tag{23}$$

Kurtosis describes the peak or flatness of the signal distribution.

$$g_{kurtosis} = \frac{N \cdot \sum_{i=1}^{N} (x_i - \overline{x})^4}{\left\{ \sqrt{\sum_{i=1}^{N} (x_i - \overline{x})^2} \right\}^2}. \tag{24}$$

In Equations (22)–(24), x_i is the ith member of points in the dataset $\boldsymbol{x}$, N is the number of data points in the dataset $\boldsymbol{x}$, $\overline{x}$ is the mean value of the dataset $\boldsymbol{x}$.

Malhi et al. presented the peak values and RMS for mechanical RUL prediction and analysis [161]. RMS and kurtosis values are also used as single HI to predict the RUL of equipment such as bearings [162,163], compressors [164]. The following Refs. [165,166] used the statistical features extracted from time-domain signals to realize the RUL prediction. In addition, the degradation information in the frequency domain signal, such as the power density, the average amplitude, and so forth, could also be used as a single HI to predict the RUL of gears, thrust bearings, and pumps [167–169]. Hanachi et al. proposed two model-based performance indicators—heat loss and power deficit—as single HI to monitor the performance degradation of gas turbines [170]. Other kinds of literature have completed a lot of models and analysis researches on a single HI [158,171,172]. However, the equipment uniqueness of a single HI cannot be extended to other systems and completely describe the degradation characteristics of the complex system, which limits its application in MSAE.

4.1.2. Synthesize HI

Many MSAE are systems composed of multiple components, and the complexity improvement leads to the lack of dominant failure features. Therefore, it will be challenging to describe the changes in system functions with a single HI. Although multiple single HIs could be used for separate analysis, it usually leads to a large deviation from RUL prediction. Consequently, it is an effective method to reasonably fuse all sensor signals related to degradation into one dimension to construct the synthesized HI [173].

Synthesize HI construction can be divided according to whether the method is optimized or not. Baraldi et al. used EMD and auto associated kernel regression model to combine different features to reflect the weighted sum of HS, which is a non-optimization-based method [174]. Loukopoulos et al. applied the PCA method to build synthesize HI for compressor valve failure, hoping to reduce information loss [175]. Zhou et al. used reduced kernel recursive least squares simplified kernel recursive least squares algorithm to build synthesized HI [176]. To overcome the problem that the trend of some HI is not obvious in the whole life cycle and could not be used to predict RUL, Liao et al. proposed genetic programming method to automatically find the high-level features in degraded signals and improve the monotonicity of HI [177]. Compared with non-optimization methods, the optimization-based methods focus on the construction of HI according to the needs of their respective models, to purposefully improve its service performance and make it a more efficient HI construction method.

Different fusion methods of synthesizing HI are divided into two categories: data-level fusion and feature-level fusion. Data-level fusion directly fuses the measured multi-sensor information into 1D, which can more accurately describe the health condition of the system than a single sensor signal. Yan et al. developed a data level fusion method to fuse multiple sensor data under multiple operating conditions into one synthesized HI to describe degradation [178]. Feature level fusion integrates the feature information generated by independent analysis methods. A priori knowledge about degradation mechanisms and physical laws is usually employed to create the required features. Liu et al. applied the feature level fusion method cascade correlation neural network to multi-sensor data fusion [179]. In contrast, the synthesized HI constructed based on data level fusion is more conducive to health condition visualization and more suitable for degradation model and RUL prediction [158].

Most fusion methods constructed synthesize HI by the linear combination of original sensor signals [178,180–182], but for more and more complex systems, multi-sensor signals usually have multiple sources and are affected by various degradation factors. Therefore, nonlinear fusion models have attracted more and more attention. Zhang et al. proposed an HI construction method based on a profound multilayer perceptron revolution neural network, which considered outlier regions simultaneously [183]. Hong et al. used wavelet packet–empirical mode decomposition combined with self-organization mapping neural network to construct confidence value as HI to realize performance degradation evaluation and RUL estimation [184]. Upadhyay et al. utilized the Gaussian mixture model and Jensen-Rényi divergence to construct the HI to ensure monotonicity when bearing conditions deteriorate [185]. Yu et al. used the automatic encoder based on a bidirectional recurrent neural network to convert the run-to-failure data of multiple units of the same system collected by multiple sensors to construct one-dimensional HI to reflect the health degradation mode [186].

The traditional data fusion method requires the researchers to determine the relevant characteristics in advance. Khanh et al. developed the method of HI automatic construction based on genetic programming, which reduced the user's preliminary work [187]. The method could be widely used in practical work and is also an essential direction of synthesizing HI development in the future.

4.2. HS Division

The degradation curve constructed by HI could reflect the change of degradation trend with different fault severity in the life cycle. According to the changes, the health condition can be categorized into different stages. Therefore, various FD and RUL predictions methods are applied to different degradation stages. This section mainly analyzes the division of degradation stages and the determination of degradation starting and ending points.

4.2.1. Degradation Stage

According to the changing trend of HIs, the degradation processes of MSAE could be divided into different HSs. HS can intuitively show the degradation process of the system, which is helpful to guide the selection of RUL prediction methods. At present, there are mainly three different forms of degradation for dividing HS in most literature, namely single stage, two stages, and multi-stages, as shown in Figure 10.

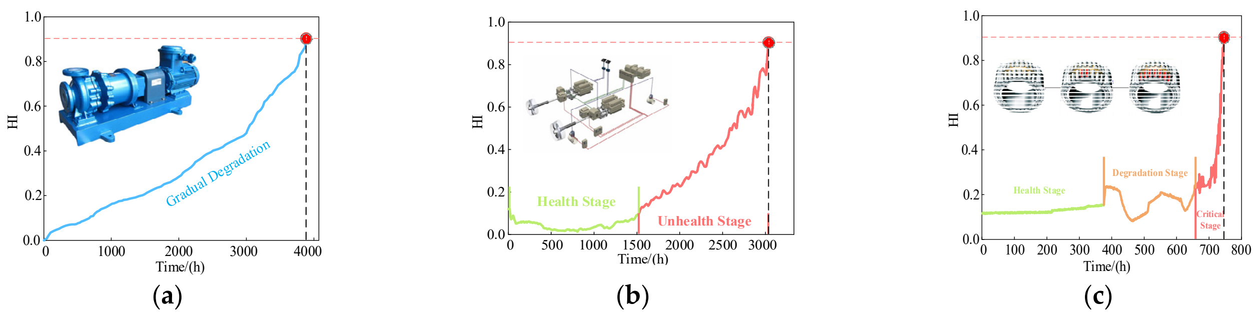


Figure 10. Different HSs: (**a**) one stage of specific equipment and (**b**) two stages of some systems and (**c**) three stages of bearings.

Figure 10a shows only a single gradually increasing trend from health to failure, indicating only a single HS in the degradation process. Therefore, it can be modeled with a single degradation model, and RUL prediction can be realized.

The degradation trend in Figure 10b shows two different stages, the HS at the beginning of the operation and the fault stage after a period of operation. At present, the HS of most MSAE can be divided according to this type. According to the delay time concept, Wang et al. defined a two-stage fault process: steady development and rapid increase, and studied the method of identifying the starting point of defects [188]. Wang et al. applied a two-stage degradation method to distinguish between health data and degraded data to avoid the interference of health data on RUL prediction accuracy [189]. Qian et al. detected fault occurrence according to a two-stage alarm threshold combined with the AR model and Kalman filter [190]. Georgoulas et al. improved the accuracy of two-stage division by using the method of adaptive alarm threshold [191]. Through the division of two-stage health status, we can see that the data in the HS does not show the trend related to degradation. The fault and RUL prediction analysis shall be carried out when the system and equipment begin to fail. Therefore, a series of unnecessary modeling and calculation for the analysis of HS data can be avoided. Because of the situation, HS is used to detect the initial machinery degradation and define it as the first prediction time (FPT) to guide the start of the RUL prediction process.

The two-stage division is only applicable to the case where the trend of machinery in the degradation stage is consistent and can be represented by a single degradation model. However, changes in operating conditions or failure modes will affect the degradation trend of machinery, so it may be necessary to further divide it into three or more HSs according to the degradation. As shown in Figure 10c, the HS is divided into three stages: health, degradation, and critical. Kimotho et al. divided the degradation process of bearings into several different stages [192,193]. Hu et al. defined four HSs for generator bearing: excellent, good, alert, and dangerous according to the degree of deterioration [194]. Hong et al. determined four different degradation stages according to the confidence value (CV) of health state and the change rate of CV and developed different prediction models according to different HSs [195]. In addition, the clustering algorithm [196–198] and the AI classification method [199–203] are also applicable to the division of different HSs and have achieved good results. A single model is not enough to express its degradation process when performing failure analysis and RUL prediction on equipment with three or more HSs. It is necessary to establish corresponding models according to the different degradation characteristics of each stage.

4.2.2. Time-to-Start and Failure Threshold

The analysis of the degradation stage can guide the selection of appropriate methods or models. When starting RUL prediction, it is necessary to set the time-to-start as the prediction starting point while according to a failure threshold to set the prediction ending point to ensure the implementation of the RUL prediction process. Therefore, the prediction start time and end thresholds are also an urgent problem to be solved in failure prognostics.

(1) Time-to-start (TTS)

The starting point of prediction is to determine the beginning of the prediction process. The data before this time is usually used as training samples to predict the health condition after this time. Therefore, selecting an appropriate prediction starting point can avoid the interference of health signals to the model or the loss of key information and improve the RUL prediction efficiency. However, due to the influence of noise and random occurrence of early faults, a more accurate method is needed to determine the appropriate starting point of prediction. Zhang et al. used the system degradation state model to detect the deviation between the baseline and corresponding current distribution and identified the fault starting point with the specified confidence and false alarm rate [204]. Yang et al. used the first CNN model and the proposed 3/5 principle to identify the initial fault point [205]. Li et al. proposed an adaptive prediction starting point selection method based on 3σ interval [206].

(2) Failure threshold

The failure threshold is the endpoint of RUL prediction. It is considered that the equipment cannot meet functional requirements when the degradation curve exceeds the fault threshold. The determination of fault threshold plays a key role in the accuracy of RUL prediction. It is usually defined as degradation reaching the predetermined limits set by experts. However, due to the impact of uncertainty, it is difficult to determine the failure threshold. Yu et al. divided the health state into two stages and added a false alarm trigger mechanism [207]. Li et al. used the probability trigger mechanism to determine the alarm threshold [208]. Shakya et al. combined Chebyshev inequality and Mahalanobis distance to determine failure threshold [209]. Alkan et al. applied the PCA method based on the variance-sensitive adaptive threshold to overcome the problems of false alarms caused by using a fixed threshold [210]. Moreover, some studies had shown that the failure threshold was not clearly defined and may be probabilistic, and the possibility of using a probabilistic failure threshold was beneficial [152,211].

4.3. RUL

RUL estimates the remaining service life of a component or system that can operate according to its expected function before maintenance or replacement [212,213], which is $RUL_k = t_{eof} - t_k$, where t_k is the current time, t_{eof} is the end of life of the equipment, and RUL_k is the RUL at t_k. An important feature of ship intelligence is self-awareness and self-prediction ability, in which RUL prediction plays an important role. RUL prediction is currently the core part of system PHM and CBM [214]. The major task of RUL prediction is to forecast the time left before the machinery losses its operation ability based on the condition monitoring information. It is the last technical process as well as the ultimate goal of machinery HP [154]. MSAE is a kind of system with low frequency and high consequences. Accurate RUL prediction of MSAE can predict the safe operation of the ship and the time when the system equipment performs its expected functions, and then guide it to achieve predictive maintenance to reduce expensive unplanned maintenance [215–217]. The main difference between its RUL prediction and other engineering systems lies in its complex working environment and diverse operation modes [218]. Commercial shipping currently relies more on inefficient, traditional time-based maintenance procedures, resulting in poor economical and labor-intensive [212]. Ship failure and shutdown caused by MSAE failure will bring potential safety hazards and cause substantial economic losses. Appropriate maintenance actions can be arranged in advance through a practical PHM framework, timely detection of failures, and effectiveness to avoid catastrophic failures and reduce maintenance costs [219].

RUL prediction process could be realized through direct and indirect methods [175,220–222]. The direct calculation process takes the machine history and current information as input to establish the relationship model between information and RUL. This method does not need to determine the fault threshold in advance and can directly estimate RUL. The indirect calculation process first needs to determine the failure threshold, establish the HI and health condition model, and finally calculate the time when HI reaches the threshold.

Based on different technologies and methodologies, we subdivide the methods of RUL prediction into three different categories, that is, degradation model methods, machine learning model methods, and hybrid model methods [223–226], as depicted in Figure 11.

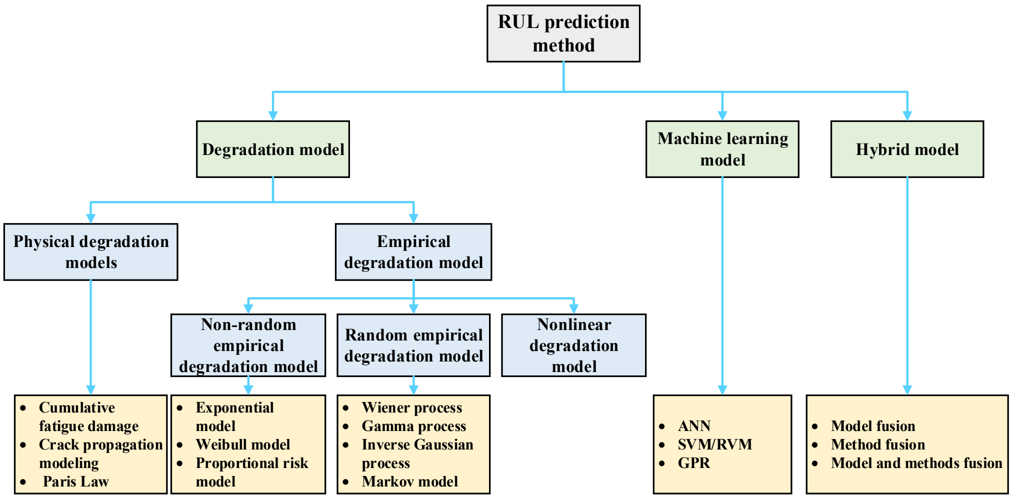


Figure 11. Summary of RUL prediction methods.

4.3.1. Degradation Model

The physical degradation model simulates the degradation process through the nominal life model. The general application depends on the model understanding of the physical process and potential system degradation characteristics [153,213]. The empirical degradation model is a data-driven model for statistical analysis through a large number of monitoring data. The advantages and disadvantages of these two methods are summarized and analyzed below.

(1) Physical Degradation Models

Based on the physical degradation model, the RUL prediction method needs to consider the different operation modes and environmental conditions. The physical meaning of equipment degradation and professional theory were used to create failure mode, which is employed to estimate the RUL [117,152,227]. When using this method, it is vital to understand the fundamental physical model of the system for calculating the damage rate and its accumulation process over time. The physical degradation model could obtain higher accuracy RUL prediction results when the equipment is relatively simple, and the degradation is caused by a single degradation factor.

The common prediction based on the physical model is crack propagation modeling. Li et al. used lognormal random variables to establish a random defect propagation model based on the deterministic defect propagation rate model for RUL prediction [228]. Li et al. employed a physical model method based on Paris law to predict the residual life of gear fatigue cracks [229]. Daigle et al. established a detailed physical model of a centrifugal pump to describe its degradation process [230]. Oppenheimer et al. established a life model based on the Forman crack propagation law of linear elastic fracture mechanics for machine RUL prediction [231].

The main advantage of this method is to realize the RUL prediction from the dynamics of the equipment degradation mechanism. If the model parameters have a one-to-one mapping relationship with physical coefficients, better degradation description and accurate prediction results could be obtained [94]. Nevertheless, the degradation models vary with equipment or systems, so the application of the method is limited. The modeling process also involves much professional knowledge, and it may be necessary to use assumptions and expert knowledge when describing the operation process and estimating parameters. In addition, mathematical models are usually expressed by complex differential equations or partial differential equations, which require a powerful computational solver and high computational cost [224]. Moreover, the difference of internal materials, the complexity and diversity of the external working environment, and the interaction of various components result in difficulty fully understanding the actual physical process of degradation and establishing an accurate physical model for RUL prediction [232–235]. Therefore, the physical degradation model is mainly used for RUL prediction modeling of simple equipment such as fan, bearing, and pump in the practical application of MSAE.

(2) Empirical Degradation Model

The empirical degradation model—also known as the degradation model based on a statistical method—is a degradation mechanism model summarized by technicians in the process of long-term use. It does not necessarily have physical significance. The empirical degradation model can obtain the probability distribution of life or remaining life by modeling the monitoring data compared with the physical degradation model. It is convenient to quantify the uncertainty of life or remaining life [236]. Si et al. [237] and Sikorska et al. [152] summarized the statistical data-driven methods used in RUL prediction, divided into a non-random empirical degradation model and stochastic empirical degradation model.

The non-random empirical degradation model ignores the internal mechanism of equipment degradation, adopts typical distribution curves, including the Exponential model [238–240], Weibull model [241], Proportional hazards model [242], and so forth. The advantage of this model is to describe the degradation trend of the equipment through the regression model and predict the RUL of equipment by extrapolation. However, its disadvantage is that the degradation trend model based on experience is arbitrary and uncertain.

The stochastic empirical degradation model fully considers the influence of uncertainty in the degradation process [214] and can describe the random time variability in the process of equipment degradation. Many stochastic empirical degradation models have been used for RUL prediction, including Wiener process [243–246], Gamma process [247,248], Inverse Gaussian process [249–251], Markov model [219,252–258]. The Wiener process has good physical and mathematical properties and can explain the time variability and nonmonotonic process of the degradation process. However, due to its dependence on the Markov hypothesis, and mainly focuses on the current degradation level and ignores the historical data, resulting in inaccurate RUL prediction. Gamma process and Inverse Gaussian process are limited to Markov condition, which can only simulate monotonic degenerate trajectory, resulting in an impractical model. Markov model is suitable for describing multi-stage transition process in the degradation process, but it is difficult to obtain training samples in different degradation stages in practical application. The advantage of the stochastic empirical degradation model is that it can obtain the analytical expression of RUL. However, it needs to use the advanced stochastic process theory for mathematical derivation, which is not conducive to the application and promotion in MSAE, the model parameter identification is difficult, and the prediction accuracy needs to be improved. In addition, the degradation trend model based on experience is arbitrary, and it is difficult to explain the degradation mechanism when the results are inaccurate.

In practical application, the mechanical system usually presents a nonlinear degradation process. Therefore, in addition to considering the uncertain influence in the degradation process, it is necessary to establish a nonlinear degradation model to describe the degradation process of machinery [259,260]. Li et al. used an exponential model to represent the nonlinear degradation process, but this method is only effective for the exponential degradation process [206]. Liu et al. responded to the nonlinear degradation process by introducing acceleration factors and predicted RUL combined with the linear autoregressive model [261]. Zio et al. described the nonlinear degradation process using the Paris Erdogan model and predicted RUL using the PF algorithm [262]. Si proposed an adaptive nonlinear prediction model and considered the influence of uncertainty for RUL prediction [260]. Gasperin et al. proposed a statistical method to extract features from vibration signals, build a dynamic model and predict its evolution with time to estimate when the gear reaches the critical stage [167].

However, this method has great limitations, which include: (1) the reliable data not being available; (2) the influence of multiple failure mechanisms of the engineering system; and (3) the mismatch between component failure distribution and model distribution. The statistical method may overlook the failure mechanism or imply that there is only a single failure mechanism of the equipment or system, which is inconsistent with the real complex engineering system's reality, which will affect the accuracy of RUL prediction [213].

4.3.2. Machine Learning Method

Due to the complexity of MSAE and the diversity of equipment, there are great differences between different ships. MSAE is usually composed of multiple components with multiple failure modes. It is almost impossible to understand all potential failure physics and their interactions of complex systems [153]. Consequently, the model-based method has some limitations in this field. With the development of modern sensor systems and data storage and processing technology, the RUL prediction method based on machine learning has been widely used and popularized. The following is a review of common machine learning methods.

(1) ANN

A variety of neural network models have been applied to RUL prediction [220]. Tian et al. constructed an ANN model with historical age and multi-state monitoring measurements as inputs and life percentage as output for more accurate RUL prediction of pumps [263]. Gebraeel et al. established an ANN model and applied the degradation signal database to realize the RUL prediction at any time during the service life of the bearing [264]. Mahamad et al. used the feed-forward neural network (FFNN) model based on Levenberg Marquardt's (LM) training algorithm to predict the RUL [265] Vachtsevanos et al. developed a dynamic wavelet neural network prediction model [266].

In addition to typical neural network models, many deep learning models have been developed for RUL prediction. Yang et al. used the dual CNN model to intelligently predict RUL only using the original signal [205]. Cui et al. proposed an adaptive performance degradation assessment method of marine turbochargers based on component generalized feature mapping [267]. Zhang et al. used long short-term memory (LSTM) recurrent neural networks (RNN) to predict RUL independently of offline training data and can predict RUL earlier than traditional methods when offline data are available [268]. Sun et al. used the deep TL network based on SAE to transfer the SAE trained by historical fault data to a new object, and RUL predicted the new target without supervision information [269].

The ANN method can achieve good results in tendency, monotonicity, and scale similarity. It often uses a signal processing method to extract equipment degradation features, and then uses the deep learning method to learn the mapping relationship between health indicators and degradation key features, to realize equipment RUL prediction. However, the neural network method is a typical "black box" model, which has low transparency and needs a large number of high-quality training data. The nodes and weights also need to be preset manually or optimized by using the optimization algorithm, which reduces their generalization ability in different situations.

(2) SVM/RVM

The least-squares SVM (LS-SVM), OC-SVM, and multi-class SVM have been successfully used in RUL prediction. Dong et al. proposed a bearing degradation prediction method based on PCA and optimized LS-SVM [270]. Carino et al. realized RUL prediction of equipment through OC-SVM [271]. Islam et al. modified LSSVM into OC-LS-SVM based on Bayesian inference-aided for accurate TTS point detection and applied recurrent least-square support vector regression (RLS-SVR) model for robust RUL estimation by predicting the future degree-of-defectiveness HI (DDHI) value [272]. Benkedjouh et al. presented isometric feature mapping to construct the HI and forecasted it using an SVR method to estimate the bearing RUL [273]. However, it is difficult to determine the penalty coefficient of SVM, and the kernel function must satisfy the Mercer theorem. To overcome the shortcomings of SVM, a supervised learning RVM is developed as its alternative method. In addition to the unrestricted use of any kernel function, its advantages also include the automatic estimation of complex parameters without cross-validation, the generation of a probability output, and the use of Bayesian approximation to solve the uncertainty of prediction in SVM.

Define a set of input data $\{x_i, t_i\}_{i=1}^{N}$ where x_i is the input variable vector, t_i is the target value, N is the length of the data, the RVM regression can be indicated as

$$t(x) = \sum_{i=1}^{N} \omega_i K(x, x_i) + \omega_0 + \varepsilon_n, \tag{25}$$

where $\boldsymbol{\omega} = [\boldsymbol{\omega}_1, \boldsymbol{\omega}_2, \cdots, \boldsymbol{\omega}_N]$ is the weight, ω_0 is the bias, $K(x, x_i)$ is kernel function, and $\varepsilon_n = N(0, \sigma^2)$ is error term with zero mean Gaussian process and variance σ^2. The Gaussian kernel function is usually preferred and given by

$$K(x, x_i) = \exp\left[-(x - x_i)^{\mathrm{T}}(x - x_i)/2S^2\right], \tag{26}$$

where S^2 is the width. More details of the algorithm can be found in the Ref. [274].

There are mainly three different RVM training algorithms: sequential sparse Bayesian learning, MacKay iterative learning, and Expectation-Maximization (EM) iterative learning algorithm. An EM-RVM algorithm is used to predict the RUL of lithium-ion batteries in hybrid vessels, which can monitor its health and prevent the occurrence of failure [213]. Wang et al. used RVM to establish the prediction degradation curve in the statistical and sparse form [159]. Widodo et al. applied the data running to fail to predict the survival probability of a single unit of machine components through the RVM model [275]. Relevance vector machine (RVM) is a sparse probability model based on a Bayesian training framework, which can overcome the shortcomings of SVM. At the same time, RVM can deal with high-dimensional, nonlinear, and small samples and provide probability prediction. It has the advantages of good sparsity, generalization ability, and high prediction accuracy. These advantages make it more suitable for solving the problems of prediction with multiple uncertainties in MSAE and difficult to obtain training samples.

(3) Gaussian process regression (GPR)

GPR is a nonparametric method that does not need to assume the candidate model structure in advance. Otherwise, the GPR method has advantages in life prediction when data are unreliable, noisy, or missing. Up till now, this model has been mainly applied in the prediction of bearing and battery life. BošKoski et al. used Rényi entropy to extract the degradation characteristics of the bearing and input it into the GPR model to predict the RUL of the bearing [276]. Yu firstly decomposes the battery capacity curve by empirical mode decomposition (EMD), then uses different GPR and logistic regression for the decomposed natural mode function and residual part, respectively, and finally adds the results of the two parts to predict the remaining life of the battery [277]. Wang et al. selected the signal peak value and its position feature after wavelet transforms as the input of GPR and effectively predicted the battery's remaining life [278]. Kong et al. combined radial basis function KPCA and GPR to predict RUL [279]. Liu et al. used the improved GPR method to realize multi-step ahead RUL prediction [280].

In general, the machine learning method relies on massive historical information to establish a model and predict RUL. It has high flexibility, does not need a lot of professional knowledge and detailed understanding of the exact degradation law, and has low requirements for the physical knowledge of the inherent fault mechanism of the system. It is suitable for complex equipment with a limited understanding of the physical level of the system, such as diesel engines in MSAE. Although machine learning models have some advantages in practical application, there are also several problems in the implementation of these models. First, it is difficult to accurately define the fault threshold due to the nonlinear nature of degradation caused by the uncertainty of the environment, load, and self-degradation. Second, the training machine learning algorithm is facing the challenge of a lack of running to the fault data set. In most cases, obtaining the actual MSAE fault data is usually time-consuming and expensive, and generally, no data set can reflect the real fault evolution.

4.3.3. Hybrid Failure Prognostics

Similar to the fault diagnosis model, the hybrid method, which combines the degradation model and prognostics method, overcomes the problem of a single degradation model or prognostics method that could not accurately predict the health condition. The hybrid method can use their advantages and makeup or minimize their weaknesses [224,281,282]. Therefore, the hybrid of signal processing, degradation model, and prediction method is a new trend in RUL prediction. According to different hybrid contents and forms, hybrid methods mainly include degradation model fusion, prediction methods fusion, and degradation model and prediction methods fusion.

(1) Degradation Model Fusion

To better describe the different degradation trends of equipment in different degradation stages, different models are used to describe different degradation processes, which is more in line with the actual degradation situation. Man et al. used the Wiener process with drift and PH model for constructing the models of stochastic degradation signals and time-to-event data, respectively, to predict the RUL [226]. Lu et al. combined the physical law of crack propagation, Paris equation, and measurement model to build a failure precursor process model for RUL estimation [283]. Peng et al. studied the inverse GPR model with a random effect for RUL prediction using the general Bayesian framework [284]. Lei et al. established the RUL prediction model based on the fusion of stochastic process and Kalman particle filter (KPF) algorithm [214]. Wang et al. established a Bayesian method for the Wiener process with change points considering measurement error [285]. Considering the influence of degradation mechanism and other factors, Yan et al. proposed a Wiener process model based on two-stage physics to describe the two-stage degradation process accurately and then predict RUL [286].

(2) Prognostics Method Fusion

Prognostics method fusion has achieved good application in the prediction of battery remaining life. Ma et al. presented a hybrid neural network model to determine the hidden degradation function and predict the RUL of lithium-ion batteries [287]. Wei et al. used the particle filter (PF) method to dynamically update the hyperparameters of the SVR model, overcome the disadvantage of poor prediction ability when there are significant differences between the training set and test set, and improve the robustness and generalization ability of the model [288]. In addition, it has also achieved good results in the fields of air compressor, bearing and so on. Loukopoulos et al. integrated SOM, Multiple Linear Regression (MLR), and Polynomial Regression (PR) models to estimate the RUL of reciprocating compressor [175]. Niu et al. used a neural network to fuse the features extracted from the signal at the feature level, then used smoothing and wavelet decomposition to denoise, and used multivariate nonlinear model regression to predict the time series when the deterioration curve triggered the alarm threshold, to realize the HCM and RUL prediction of the compressor [289]. Ding et al. proposed a kernel regression depth transfer metric learning method and successfully applied it to RUL prediction of bearings under multiple working conditions [290].

The above method successfully solves the single-point prediction of RUL. However, because the prediction method will be affected by various sources of uncertainty, such as operation uncertainty, modeling uncertainty, and prediction method uncertainty, the method based on point estimation alone cannot provide sufficient confidence for the prediction results, resulting in inaccurate results. Therefore, in the prediction method of MSAE, it is very necessary to explain and quantify the prediction uncertainty and improve the prediction results. To solve this problem, Wang et al. proposed the fusion of two Bayesian models to provide a probability distribution for the uncertainty in the final prediction results, and the framework is shown in Figure 12 [143]. The Bayesian theorem can be expressed as

$$p(w|X,Y) = \frac{p(w)p(Y,X|w)}{p(Y|X)} \tag{27}$$

where (X,Y) is the observed variables, w is the unobserved parameters.

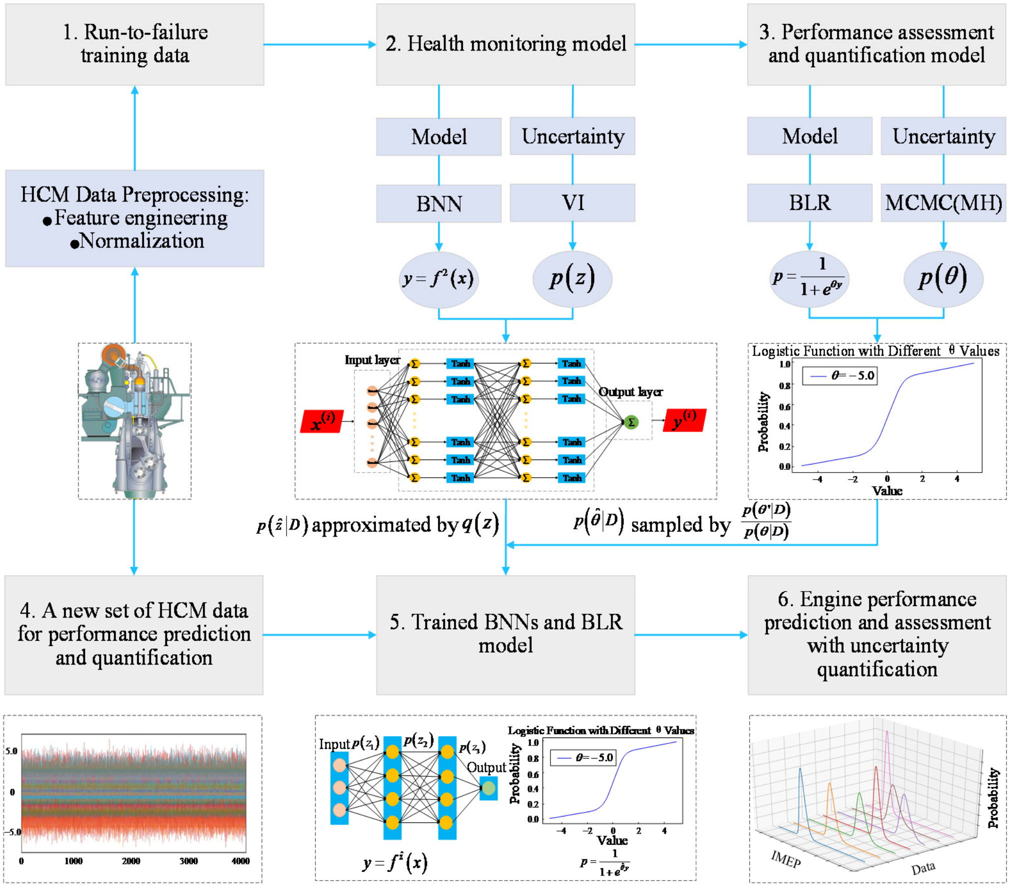


Figure 12. Application of hybrid performance prognostics to diesel engine.

Firstly, the diesel engine HCM data are preprocessed to extract the required training set and test set data. Secondly, through the indirect estimation method, Bayesian neural network (BNN) is used to model the relationship between HCM data (IAS signals) and HI data (IMEP data), so as to realize the diesel engine health monitoring and prediction process. The model consists of an input layer, two hidden layers, and an output layer.

There are n sets of HCM data $\boldsymbol{D} = \boldsymbol{X}, \boldsymbol{Y}$ corresponding to the input features of IAS signals $\boldsymbol{X} = \{x^i\}_{i=1}^n, x^i \in R^{1\times m}$ and the output value of IMEP $\boldsymbol{Y} = \{y^i\}_{i=1}^n, y^i \in R$. The parameters z of BNN model are then trained by x^i and y^i. The new output value $\hat{y}^{i+1}$ could be expressed as

$$\hat{y}^{i+1} = \int f\left(x^{i+1}, z\right) p(z|D) dz \tag{28}$$

According to the VI algorithm, a variational distribution $q(z)$ is approximate to the true posterior $p(z|D)$, so the $\hat{y}$ could be written as

$$\hat{y}^{i+1} \approx \int f\left(x^{i+1}, z\right) q(z) dz \tag{29}$$

where f is the nonlinear activation function.

Then Bayesian logistic regression (BLR) model is used to model the predicted HI data, and the degradation performance with uncertainty is evaluated and quantified with a confidence interval to generate a series of possible final results rather than a single prediction value.

The input of BLR model is the IMEP value y^i, and output c^i is a Bernoulli variable where the normal condition is 1 and the fault condition is 0. The transition expressed by percentage from normal to fault can be formulated as

$$\begin{aligned} p(c|y,\theta) &= Bernoulli\left(\frac{1}{1+e^{\theta y}}\right) \\ &= \prod_{i=1}^{N}\left(\frac{1}{1+e^{\theta y_i}}\right)^{c_i}\left(1-\frac{1}{1+e^{\theta y_i}}\right)^{1-c_i} \end{aligned} \tag{30}$$

where $\theta y_i = \alpha + \beta y_i$, α and β are the process parameters, y_i is the predictd value of IMEP, and the binary output is $c_i \in 0, 1$.

Variational inference (VI) and Markov Chain Monte Carlo (MCMC) are used to train and infer the relevant parameters in the two Bayesian methods, respectively. Finally, the new data are used to train BNN and BLR models, and the optimal parameters are retained for further prediction and assessment with uncertainty quantification. This method considers the uncertainty of parameters, which can improve the prediction performance, the robustness, and prevent overfitting of the model. With the understanding of the environment, the decision made by the model becomes more deterministic, plays a significant role in condition-based prognostics, and makes the maintenance decision of marine engines more comprehensive.

In addition, another point of interest is the adaptive fusion model of automatic selection machine learning algorithm. Hu et al. summarized the shortcomings of the traditional data-driven prediction method using training data sets to construct multiple candidate algorithms and considered that a single algorithm may lack robustness and waste resources in constructing abandoned alternative methods. Therefore, a multi data-driven integrated prediction method based on three weighting schemes is proposed [153]. The future development direction is how to automatically build alternative data-driven methods and select the fusion of various methods adaptively.

(3) Degradation Model and Prognostics Methods Fusion

Tran et al. used the normal operation data to create the identification model and used the RMS of the residual for the construction of HI, combined Cox's PH model and SVM to build a fusion model of a three-stage method to predict the RUL of the compressor [164]. Yu et al. integrated Bayesian inference-based SOM, logistic regression (LR), and high-order particle filtering (HOPF) to build a data-model-fusion scheme to evaluate and predict the health degradation of the machine [291]. Aiming at the problems of incomplete historical data and lack of prior knowledge in the process of fault prediction, Zhou et al. Combined Weibull proportional risk model with the least-squares linear regression function to predict the RUL of marine diesel engines [292]. Byington et al. combined model-based and vibration-based features with data-driven methods to evaluate the current health state of the coupling and predict the RUL [293]. These methods aim to integrate the advantages of the degradation model and prognostics method for reliable machine health assessment and prediction. It not only solves the problem that the degradation model cannot directly reflect the degradation degree, and the complex parameters are difficult to define, make it is difficult to build a real model for machine degradation propagation, and is not suitable for equipment whose physical parameters and failure modes may change under different conditions. At the same time, it also solves the disadvantage that the prognostics model needs to use historical data including normal and fault operation in the training process, which are difficult to obtain in MSAE. These fusion model methods improve the applicability and accuracy of RUL prediction of MSAE.

4.4. Epilog

Although RUL prediction has been widely used and made remarkable achievements in machinery, electronics, vehicles, aviation, and so on, there are still the following limitations in applying RUL prediction in ships.

(1) Ship manufacturing is a large-scale project. The performance of MSAE put into operation is different, and even the performance parameters of the two sister ships will be significantly different. Therefore, the prediction model is not universal.

(2) Choosing an appropriate HI construction method and reasonable division of HS greatly impacts the accuracy of prediction. Meanwhile, identify the starting point of failure and failure threshold are the main obstacle to the universal application of RUL in MSAE.

(3) Due to extensive investment and low return, many ship-owners are reluctant to use the RUL prediction program.

Considering the above reasons, there are still some limitations in the application of RUL in MSAE. With the development of sensors, IoT, and big data, the collected degradation signals about equipment will be more sufficient. Therefore, the data-driven RUL prediction method and fusion RUL prediction method are the primary development direction in the future.

5. Maintenance Decision

A maintenance decision describes the O&M vision of maintaining the health and safety of assets in the whole life cycle. The specific repair process includes inspection, repair, upkeep, and renewal of the systems, subsystems, and components. In order to improve maintenance efficiency and reduce cost, maintenance strategies have also shown many types [294]. Figure 13 depicts the evolution of maintenance strategy in the maritime field.

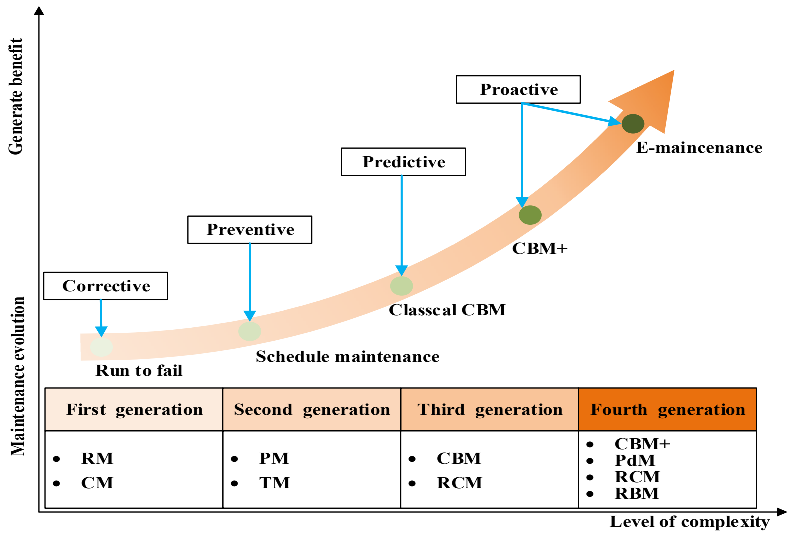


Figure 13. Evolution of maintenance strategies in the marine domain.

- The first generation maintenance method mainly adopts the run to failure maintenance method. That is, the maintenance process is operated until it breaks down. The typical maintenance practices are routine maintenance (RM), (ii) CM [295].
- Second-generation maintenance is mainly preventive maintenance. With the increasing complexity of MSAE, the maintenance cost increases. The maintenance policies adopted are (i) PM, (ii) time-based maintenance (TM).
- The maintenance strategies adopted during the period 1980–2000 are called the third generation maintenance. The typical maintenance character of this period is mainly predictive maintenance. (i) CBM, (ii) reliability centered maintenance (RCM).
- The traditional maintenance methods are transforming to more proactive types, this is the recent generation maintenance. This generation is highly characterized by the in-

ception of risk-based maintenance (RBM) in addition to RCM, Predictive Maintenance, CBM, and CBM+.

5.1. Corrective Maintenance

CM is a post-maintenance strategy. When the equipment breaks down unexpectedly due to problems, take appropriate corrective measures to restore the function of the equipment. The maintenance process mainly includes repairing or replacing faulty parts. Therefore, this strategy is only applicable to equipment whose failure consequences will not cause serious problems. The investment required to implement this maintenance strategy is much lower than any other maintenance strategy, but when applied to critical equipment, it may increase additional maintenance costs and increase downtime [296].

5.2. Preventive Maintenance

At present, a planned maintenance system (PMS) based on ISM code [297] is still widely used by shipping companies. PM is a preventive maintenance method, and operational equipment is maintained based on a certain working interval or timing. This method could effectively avoid any potential failure or severe degradation that may impact MSAE reliability in the near future.

The frequency of implementing PM work depends on the experience of marine engineers or manufacturer's instructions and recommendations. Implementing PM strategy in MSAE with high reliability can effectively reduce the failure rate and cost, prolong life compared to the CM. PM is currently practiced in merchant vessels as the most preferred maintenance strategy [298]. However, PM does not consider the health condition of the current MSAE, so this may lead to unnecessary machinery downtime and excessive maintenance problems, which include high repair costs and maintenance-induced failures [299,300]. As described in [301], time-based PM actions may result in misjudgment about the MSAE's health condition as usage is not constant over time.

5.3. Predictive Maintenance

5.3.1. CBM

CBM takes advantage of modern condition perception methods to track MSAE health state in real-time, realize fault diagnosis and failure prognostics according to DIaK, and make maintenance decisions in combination with the health state, diagnosis, and prognostics results. It is an important maintenance strategy under PHM. According to this strategy, the maintenance work will be completed when the MSAE is needed. Figure 14 compares the health stages in which different maintenance methods are performed. The goal of CBM is to reduce the cost of spare parts, system downtime, and maintenance time, which requires engineers to complete the work at the right time. Many researchers have shown that the CBM strategy is more effective than the PM strategy. It is reported in the literature that the use of CBM may extend maintenance overhaul cycles by up to 50% and save between 25% and 45% of maintenance costs [212].

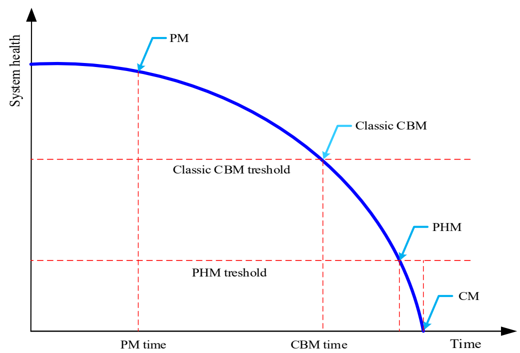


Figure 14. Health stage of different maintenance options.

Although CBM can significantly save maintenance costs and reduce failure risk, the current survey shows that only 10% of the marine industry uses CBM as the preferred maintenance strategy [302]. One of the main reasons limiting the application of CBM onboard ships is that the ship is a complex system composed of systems, subsystems, equipment, and components, whether it is the physical process and function description of the system, the analysis of DIaK, and even the formulation of maintenance decision-making need to be completed by professionals with high technical levels.

5.3.2. RCM

RCM is a method developed by the aviation industry to ensure asset availability and reliability and gradually applied to other fields [303]. The framework of RCM includes corrective, preventive, and predictive maintenance methods. Although RCM is successfully implemented in wind turbines [304], power distribution systems [305,306], transformer [307], and aircraft indicators [308], it is less used in merchant ships due to resource and cost constraints [309]. Several classifications such as Lloyd's Register, DNV GL, and Bureau Veritas have proposed to apply the RCM method to the merchant's vessel, and some provide consulting and analysis services. ABS has developed and published the RCM merchant shipping comprehensive guidance note [14]. A holistic maintenance strategy based on RCM principles is utilized to increase the operational reliability of ships [310]. RCM analyses are used to provide a process to optimize maintenance tasks and achieve optimal reliability for vessels [311]. Amendments to the RCM method were proposed for the first time for assessing maintenance needs and reliability challenges on unmanned cargo ships [312].

Despite its applicability and the potential benefits of RCM, merchant vessels often have relatively unique designs, even sister ships which can still have considerable differences in MSAE. Therefore, in most cases, the RCM successful application for one ship could not be directly used for another ship, which hindered the adoption of the RCM method onboard the ships.

5.4. Proactive Maintenance

5.4.1. RBM

RBM was developed to inspect high-risk equipment and components, strengthens inspection and maintenance, and reduces failure probability and consequences [295]. The RBM has been accepted in principle by maritime regulatory bodies, and the adoption of RBM for ships was relatively less studied. Some researchers have proposed that RBM was used for hulls and structures, and RCM is recommended for mechanical systems. Those studies [313–317] may be classified as RBM for ships.

As an important part of maintenance decision-making, RBM can be effectively improved ship availability and optimized maintenance cost. Fully implementation of RBM for future applications needs sufficient resources which are required from appropriate organizations in the maritime industry to collect DIaK.

5.4.2. An E-Maintenance

Researchers sometimes consider e-Maintenance as a maintenance strategy, a maintenance plan, a maintenance type (e.g., CBM, RCM, RBM), or maintenance support [318]. As an enterprise-level architecture, e-Maintenance includes the resources, services, and management necessary to execute proactive maintenance decisions. This support consists of two parts: e-technologies such as ICT, web technology, new sensors, wireless communications, and so forth, and the other is e-maintenance activities (operations or processes) such as e-monitoring e-diagnosis, e-prognosis, and so forth. [319].

Through the e-Maintenance, the pertinent DIaK becomes available and usable at the right place, at the right time for making the best (anticipated) maintenance decision. Although E-maintenance has not been applied in ships, it has a broad application prospect in MSAE maintenance because it can make better use of big data and modern information technology.

5.5. Epilog

Different maintenance methods have different advantages and disadvantages and are also suitable for different scenarios. Therefore, selecting an appropriate maintenance strategy plays an important role in the health management of MSAE. The least that can be concluded from the literature review is that the maintenance method of MSAE should be an advanced maintenance management technology based on e-maintenance as the framework system, CBM, RCM, and RBM as the main maintenance strategy and assisted by an intelligent algorithm.

6. Future Challenges by Intelligent Ship PHM

The intelligent ship requires PHM systems that must be owing to the ability to provide comprehensive condition monitoring, reliable diagnostics, and accurate prognostics information to adapt to the uncertainty of various working conditions. Due to the lack of crew and the use of highly automated systems, detailed end-to-end solutions are required. Although PHM has made many achievements in marine engineering, there are still many aspects that need further research. Through the research summary, we conclude that there are currently five relevant challenges included the scientific design, effective implementation, and technological innovation of PHM solutions in MSAE, which will be discussed in order.

6.1. Omnidirectional Condition Perception

Using intelligent sensor technology to build sensor networks, realize intelligent sensor layout and obtain omnidirectional condition information is the priority problem of ship intelligent O&M technology.

The performance of sensor networks is affected by the state of sensors, system health characteristics, working mode, and sensor layout. If the sensor layout is unreasonable, it will not provide sufficient motoring data, which will be unable to accurately understand and track changes in health conditions. Although using sensor saturation configuration can effectively reduce the information loss, it will obtain a large number of irrelevant or even conflicting data, resulting in the complexity of the system and increasing the cost. These effects will lead to misjudgment of system health condition [320]. Therefore, determining the type, number, and location of sensors in the limited space of MSAE to optimize the sensor arrangement is significantly important to ensure the effective implementation of PHM. At the same time, the reliability and redundancy of sensors should be considered.

6.2. DIaK Integrated Coding Technology

Modern merchant ships are consist of numerous systems, sub-systems or units, equipment, and component, which are supplied by multiple different suppliers and assembled by the shipyard. Each manufacturer uses its coding system to encode the information of mechanical equipment, and the lack of a unified coding standard makes the data interaction and data maintenance difficult between various systems. Therefore, the reasonable information classification and coding rules for the whole life cycle of MSAE have become one of the urgent problems to be solved in the development process of the intelligent ship. Unified information classification and coding can efficiently realize the transmission and sharing of equipment information in the stages of design, construction, and O&M and provide a data basis for establishing various information management systems.

6.3. Treatment of Uncertainty Problems

The health management of ship mechanical systems is affected by internal uncertainties such as working conditions and degradation, and external ones such as navigation environment and abnormal external working conditions. Therefore, the decision-making of health management should not only consider the completion of internal performance analysis but also integrate multiple external information to realize comprehensive health assessment, to make scientific operation and maintenance decisions. This external uncertainty information and its impact mainly include:

(1) Extreme weather. In extreme weather conditions such as typhoons, the mechanical system suffers an abnormal influence. For the HCM, it is necessary to solve the challenges of adaptive adjustment of the alarm threshold. In addition, these impact loads directly affect the service life of the mechanical system.

(2) Special areas for navigation. When sailing through a special area, some systems and equipment need to change the working mode to meet the requirements of the convention, which will directly affect the accuracy of fault mode identification and failure prediction.

(3) Sudden global abnormal information. These sudden problems include canal blockage, military control, COVID-19 pandemic, and so on. The current COVID-19 pandemic will directly affect the transportation of ship materials and equipment spare parts, loading and unloading goods at the port, personnel replacement. These influences will make maintenance decisions more difficult.

To address these problems, the health management of marine mechanical systems should focus on building an adaptive baseline and threshold model to adapt to complex environments and working modes, scientifically divide health stages, and improve the accuracy of diagnosis and prediction. In addition, ships need more extensive information acquisition ability to enhance the acquisition ability of accident information. Receive real-time weather and port information, use the Internet of things technology to optimize resource allocation worldwide, integrate this online information into the health management model and seek the best solution. To sum up, the integrated health management system integrating multiple information is the major problem to be solved in the future.

6.4. Proactive Perception

Different from the traditional way of using historical or real-time data, proactive perception can directly obtain time data or some specific laws of data to get deeper state information [321]. Each agent or intelligent unit in the MSAE will actively obtain the operation state data, environmental data, equipment-related information, knowledge from the intelligent knowledge base. At the same time, the DIaK will actively carry out further discovery and obtain new data to increase the information amount and information value of the acquired data.

In some cases, proactive perception should refer to certain models and rules to obtain the desired information directly from various information sources. It can also obtain short-term or interval information according to a certain pattern to realize deep judgment. The proactive perception of the equipment is further realized by the intelligent decision of the agent. For example, in real ship engine room inspection, active sensing mode can be used to trigger instead of manual inspection. The premise is to have enough perceptual information, including video, audio, vibration, conventional parameters, and system equipment-related information and supporting knowledge base.

6.5. Engineering Self-Healing and Immune System

MSAE is highly uncertain, and some equipment is only suitable for non-invasive methods. Therefore, more advanced solutions than preventive maintenance are needed to optimize resource allocation and improve O&M efficiency. Engineering self-healing and the immune system could be a suitable approach to this problem.

System self-healing includes many methods. The most common strategy is to use the redundant equipment in the system to replace the recovery function of the failed equipment. This function must be considered during MSAE design and manufacturing. The second is to unload non-essential equipment and maintain the main output function. In addition, when a single or partial component has a problem affecting the system function, use the interaction relationship among subsystems, equipment, and components in the system to adjust the function output of normal equipment and make up for the impact of faulty equipment on the system.

The engineering immune system is an analogy of the biological immune system, which protects against invasion and infection by identifying and killing the pathogens [4]. The system's goal is to achieve efficient near-zero breakdown performance with as little human intervention as possible. The system has a high degree of autonomy and can recover and maintain system functions without external interference. At present, this technology has been applied to the computer field. To further improve the health management of MSAE, further development of engineering self-healing and immune systems are essential.

7. Conclusions

This article reasonably divided the whole PHM system of MSAE into four functions. Through filtering the keywords and assessing the state-of-the-art, we had systematically reviewed more than 300 related articles in the marine field and analyzed different kinds of approaches and applications. In the HCM section, three technical means, data acquisition, data processing, and condition monitoring, were introduced in detail. The FD section summarized diagnostic methods and applications based on existing research and gave some solutions for MSAE. HP reviewed relevant implementation methods, divided the prognosis process into HI construction, HS division, and RUL, and discussed these three processes in detail. In the MD-making section, we summarized the development process of ship maintenance technology and expounded on the technical characteristics, advantages, and disadvantages of widely used maintenance methods. By summarizing the existing technologies and applications in marine engineering, it is found that there are still several aspects of being further studied in the marine field. Five urgent technical problems are proposed, including omnidirectional state perception, DIaK integrated coding, treatment of uncertainty problems, proactive perception, and engineering self-healing and immune system. It should be concerned that PHM has experienced significant development in the last decade. Affected by the particular working conditions of the ship, it is still facing problems in many theoretical and practical aspects. We consider that the summarized results and prospects provide valuable guidelines for future research for researchers in the marine field.

Although this review work has achieved numerous advancements, there are still some limitations that need further research.

(1) The matching port facilities, policies, and regulations are also the necessary elements of the PHM solutions. Due to the limitations of topic and article length, the content in this paper does not cover this part. They are also essential for the overall framework of PHM.

(2) The topics and understandings of this review are established on the current PHM literature, elaborated on the existing PHM framework technology and application. With the application of advanced techniques and intelligent O&M concepts, a future autonomous vessel may have a completely different design, requirements, and constraints. The study of autonomous ship PHM technologies will be part of our future work.

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