Transportation Safety and Environment, 2021, Vol. 3, No. 2 85–102

https://doi.org/10.1093/tse/tdab005
Advance Access publication 2021 May 14
Review

REVIEW

Review of condition monitoring and fault diagnosis for marine power systems

Xiaojian Xu[1], Xinping Yan[2,3,*], Kun Yang[2,3], Jiangbin Zhao[2,3], Chenxing Sheng[2,3] and Chengqing Yuan[2,3]

[1]China Waterborne Transport Research Institute, 100088 Beijing, China, [2]Reability Engineering Institute, School of Energy and Power Engineering, Wuhan University of Technology, Wuhan, 430063 Hubei, China and [3]National Engineering Research Center for Water Transport Safety, Wuhan University of Technology, Wuhan, 430063 Hubei, China

*Corresponding author. E-mail: xpyan@whut.edu.cn

Abstract

The use of condition monitoring and fault diagnosis (CMFD) in marine power systems significantly influences ship safety. This study divides the development of CMFD for marine power systems into three periods and reviews the content, state and limitations of CMFD research for each period. According to the research achievements and engineering experience of the authors' team, typical application cases are introduced for CMFD in ships, including CMFD platforms on engineering ships, salvage ships, container ships and ro-ro ships powered by solar photovoltaic systems. Finally, prospective research directions are proposed for CMFD in marine power systems, considering the research status of CMFD and the trend toward intelligent and eco-friendly ships.

Keywords: marine power system; condition monitoring; fault diagnosis; new energy ships

1. Introduction

As the main vehicles for global freight, ships play an important role in international trade. At present, the 55 000 merchant ships existing worldwide account for over 90% of word trade [1]. A marine power system is the heart of a ship, and consists of equipment for generating, transferring and consuming various energies. The energies provided by marine power systems ensure the safety of ship navigation [2].

Currently, over 99% of large merchant ships use marine diesel engines as the main power source; this is because the technologies for diesel engines are so mature that the reliability of the engines is essentially guaranteed. Additionally,

Received: 12 November 2020; **Revised:** 8 March 2021; **Accepted:** 19 March 2021

diesel engines start quickly, and have a wide power range and high efficiency [3].

The operating conditions of marine power systems are complicated and changeable, as the sailing conditions of ships are harsh, and ships must enter and leave ports frequently. When a marine power system works over a long term in high temperatures, high humidity, and/or corrosive and/or vibrational environments, various faults and damages will occur in the equipment of the system, with negative effects on the performance of the entire power system. According to a study on main engine damage published by the Swedish Club, claims caused by mechanical faults in ships accounted for 47% of the total ship damage claims, generating nearly 384 million USD of financial loss. More specifically, 28% of the claims for mechanical faults were from marine diesel engine faults, leading to damages of approximately 13 million USD [4]. The study indicated that marine power system faults can reduce navigation safety, lead to serious maritime accidents, and cause massive personal and property losses. Consequently, it is necessary to study condition monitoring and fault diagnosis (CMFD) for marine power systems.

The significance of CMFD techniques is as follows. First, they can effectively improve the safety and reliability of ships, so as to avoid severe accidents. Second, they can reduce the working load of the crew on board, and decrease the number of false negatives and false positives caused by crew fatigue and limited experience. Third, they can increase the operational efficiency of ships, and reduce unnecessary wastes of parts and manpower. Fourth, they can improve the limits of traditional ship maintenance, and promote changes on maintenance methods, such as from corrective maintenance and predictive maintenance to condition-based maintenance. Fifth, they provide the foundation for smart ships, including support for intelligent operations, maintenance and management [5].

Hundreds of articles on machinery CMFD techniques are published in academic journals, conference proceedings and technical reports every year. Many researchers have studied CMFD for marine power systems from both theoretical and applied perspectives. This study reviews the research on CMFD for marine power systems. The theoretical research on CMFD for marine power systems is divided into three stages: offline condition monitoring, online condition monitoring/remote fault diagnosis and intelligent fault diagnosis. As for applied research, this study describes the construction and functions of CMFD platforms for various ships. Furthermore, considering that ship construction is developing toward green and/or smart ships, the corresponding challenges in CMFD for marine power systems are proposed. With this review, readers can obtain a clear and comprehensive understanding of CMFD for marine power systems, and the application cases can be used as references for practice. Future research directions in this area could help researchers conduct additional studies.

In Section 2, the research progress on CMFD for marine power systems is reviewed. Based on the research achievements and engineering experience of the authors' team, typical application cases for CMFD on ships are described in detail in Section 3. Section 4 discusses future research directions and challenges in CMFD for marine power systems. Finally, in Section 5, the review is concluded.

2. Research progress on CMFD

With the developments in automation, reliability engineering and maintenance theory, the research progress on CMFD for a marine power system can be divided into three generations, as shown in Fig. 1. The first generation of research is mainly based on all types of field-testing techniques; the second generation is mainly based on online condition monitoring and remote fault diagnosis; and the third generation has mainly been based on intelligent fault diagnosis and intelligent patrol robots.

2.1 First generation of CMFD

In the first generation of CMFD, various techniques for signal acquisition are used to develop a variety of field-testing techniques, including performance-parameter monitoring, oil monitoring and vibration monitoring. These techniques quickly detect the operating conditions of equipment, and are suitable for periodic examinations of marine machinery. To realize accurate fault diagnosis, these acquired signals should be further processed to extract appropriate fault features.

2.1.1 Signal acquisition.

Performance parameters acquisition. In marine power systems, performance parameters are mainly applied in fault diagnoses for marine diesel engines. The performance parameters

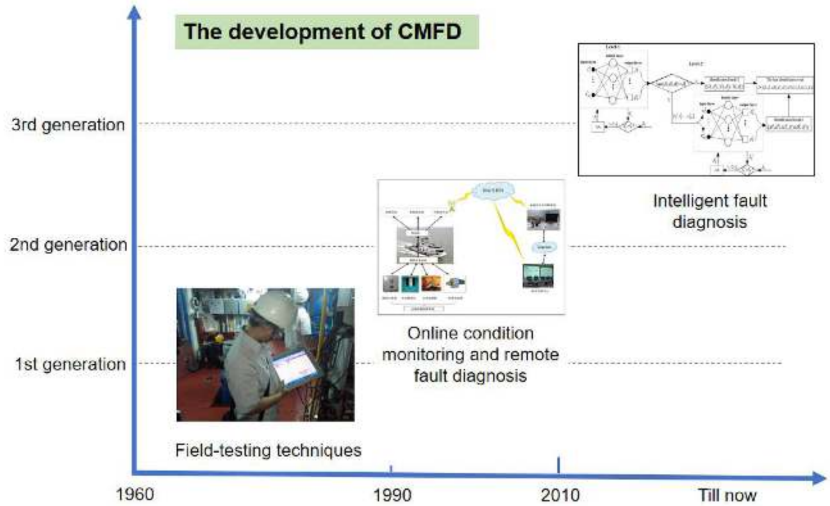

Fig. 1. Development of condition monitoring and fault diagnosis (CMFD) for marine power systems

mainly include the temperature and pressure of the media in the engines (e.g. air, fuel gas, lubricating oil and coolant) and engine power. An engine condition can be reasonably evaluated by comparing observed performance parameter values with standard values (i.e. the parameter values in the normal state).

Based on performance parameters, Kyrtatos et al. built a program library for simulating the faults of a two-stroke marine diesel engine, and used these programs to diagnose engine faults [6]. Hountalas et al. developed a fault simulation model based on performance parameters for monitoring the condition of a marine diesel engine, and identified the fault modes of the engine [7]. Zhao established a universal fault simulation model for marine diesel engines using performance parameters, and identified engine faults using a simulation model [8]. Xu et al. used ten performance parameters as fault features (including the exhaust manifold temperature and fuel consumption), and constructed a fault-diagnostic model for the exhaust turbocharging system of a diesel engine [9]. From the above references, it can be seen that fault diagnosis based on performance parameters for marine diesel engines is mainly conducted with simulation models. Using these simulation models, we could further explore how different faults affect the performance parameters. However, there are also several difficulties when performance parameters are used in fault diagnosis: (i) the performance parameters strongly influence the simulation results, and are difficult to verify through experiments; (ii) it is difficult to determine how the performance parameters will vary when concurrent faults occur in diesel engines; and (iii) it is difficult to directly acquire certain performance parameters from engines, such as the maximum temperature in the cylinder, single-cylinder cyclic oil volume and compressor flow. Currently, some commercial fault-diagnostic systems for marine power systems based on performance parameters have been applied in engineering practice, such as the pressure mean indicator system, and the 'Computer Controlled Surveillance' system developed by MAN B&W [10].

Oil parameters acquisition. Oil monitoring was conducted in the 1940s, including physicochemical analyses of lubricating oils and wear particle analyses. Testing methods for oil monitoring include routine physicochemical analysis, ferrographic analysis, spectrum analysis, particle counting and magnetic plug monitoring [11]. A physicochemical analysis can reflect the faults caused by poor lubrication, based on indicators such as the lubricating oil viscosity, density, acid value, antioxidation stability and wear resistance [12]. A wear-particle analysis can be used to evaluate the wear state of machinery, by analysing the characteristics of wear particles in the lubricating oil.

In the early development of oil monitoring, the methods for acquiring oil parameters were mainly offline and portable. Offline methods have high detection precision based on using testing instruments in laboratories, but the testing time is quite long. Therefore, they cannot monitor the conditions of the lubricating oil in real time. As a consequence, the best time for changing the failing lubricants will be missed. In contrast, portable methods have a short testing period, and can quickly evaluate oil conditions in the field. Peng et al. analysed the number, distribution and morphology of wear particles using instruments in a laboratory, and detected faults in rolling bearings [13]. Du et al. designed a portable oil-monitoring device for measuring the physicochemical properties of oil. The device contained a four-in-one sensor, a moisture sensor and a ferroelectric sensor. The four-in-one sensor measured the oil viscosity, density, dielectric constant and temperature. Using this device, they quantitatively explored the ageing process of lubricating oil from different perspectives [14]. Agoston et al. used a thickness-shear-mode microacoustic resonator to develop a sensor for monitoring the viscosity of engine oil. The sensor was suitable for detecting oil viscosity changes caused by thermal deterioration [15]. The MiniLab oil-monitoring system produced by Spectro can monitor the key parameters of wear particles and physicochemical parameters of lubricating oil. The device can achieve high monitoring precision in the field, as well as in the laboratory [16]. However, with the development of sensor technologies, the general trend is toward online oil monitoring [17].

Vibration parameters acquisition. In the equipment of a marine power system, structural gaps are caused by installation errors, manufacturing deviations and abrasions. These gaps can cause the mass of the moving components to become unbalanced, leading to the generation of centrifugal force. The centrifugal force can cause vibrations in the moving components. Features describing the vibration include the displacement, velocity, acceleration, frequency and phase. Different vibration features are generally selected for different application scenarios. For example, the displacement is generally collected by a displacement sensor for low-frequency vibrations, whereas the acceleration is collected for high-frequency vibrations.

In recent years, research has indicated that the internal faults of diesel engines in marine power systems can be located accurately and diagnosed quickly using the acquired vibration parameters acquired. Guo et al. successfully collected vibration signals from an engine body, and used them to successfully detect a wear fault in a cylinder linear-piston ring [18]. Nag et al. added hydrogen into the fuel of a diesel engine to explore how hydrogen affects the operation of the engine, and collected the vibration signals under different rotating speeds and frequencies [19]. Xu et al. studied the correlations between the inherent vibration modes of a cylinder head and excitation frequency of a diesel engine, providing a theoretical basis for determining the installation locations for vibration sensors [20].

2.1.2 Fault feature extraction.

Feature extraction from wear particles. The characteristics of the wear particles in lubricating oil are mainly extracted by processing wear-particle images, which are further used to determine the wear states and wear faults of the equipment in marine power systems. Thomas et al. (Swansea University) proposed a boundary chain code for digitally representing the characteristics of wear particles [21]. Uedelhoven et al. took two-dimensional pictures of particles with an optical microscope, and explored the relationships between these wear particle pictures and different wear states [22]. Beddow analysed typical wear particles, and used a Fourier series to extract the characteristics of wear particles, such as their roundness, long axis, short axis and irregularity [23]. Podsiadlo et al. studied the fractal features of wear particles, digital characterization methods, and the variable-scale properties of particle images [24]. Peng et al. used a confocal laser scanning microscope to collect wear particle images, and extracted the surface roughness and texture parameters of the wear particles to describe their three-dimensional morphology [25]. Wu et al. proposed a new method for describing wear states using online ferrographic images, and studied the colours of different wear particles in online images. Three common metal wear debris types were distinguished based on colour [26].

Feature extraction from vibration signals. The three main feature extraction methods for vibration signals are a time domain analysis, frequency domain analysis and time-frequency domain analysis. Time domain features include dimensional parameters (e.g. standard deviation, variance, maximum and minimum amplitudes, root mean square value and mean square error) and non-dimensional parameters (e.g. skewness, kurtosis, crest factor and corrugation factor). A frequency domain analysis can reflect the correlations between the operating conditions of machines and their vibration signals through a visualized spectrum analysis. A time-frequency domain analysis can include, for example, a short-time Fourier transform, Wigner-Ville distribution, wavelet transform or empirical mode decomposition (EMD). Time-frequency domain analyses can process non-linear and non-stationary vibration signals, thereby conforming to the actual working conditions of marine power systems. Considering the reciprocating and rotating characteristics of marine power systems, many studies have been conducted on extracting fault features from vibration signals. In Ref. [27], vibration signals were decomposed into wavelet package components; then, time-domain fault features were extracted from the reconstructed time series and used to diagnose faults in reciprocating machinery. Nikula et al. filtered the vibration signals of a low-speed bearing and divided the signals into short time windows, from which the time-domain features were extracted [28]. Liu et al. proposed a new fault detection method based on the time-domain features of vibration signals, and located a failing gear in a gearbox based on these fault features [29]. He et al. combined singular value decomposition with wavelet package decomposition to extract energy features of different frequency bands from reconstructed vibration signals, and the newly proposed method was successfully applied in a fault diagnosis of pumps [30]. Cheng et al. used EMD to decompose vibration signals into several intrinsic mode functions, and extracted fault features based on the Hilbert marginal spectrum, intrinsic mode functions (IMFs) and IMF envelope spectrum [31].

2.2 Second generation of CMFD

Owing to the progress in sensor, computer and network communication technologies, the CMFD for marine power systems has developed toward online and networked systems. Many research institutions and scholars emphasize online condition monitoring and remote fault diagnosis; in this context, the second generation of CMFD has emerged.

2.2.1 Online condition monitoring. Online condition monitoring meets the demands for real-time fault diagnosis. The monitoring and alarm system in a marine engine room is an important part of engine room automation. Using the monitoring system, the operational parameters of the equipment in the engine room are monitored in real time, and abnormal states in the equipment can be detected during the intervals between two checks. Many companies from France, Germany, the United States and Norway have developed fault-diagnostic systems for marine diesel engines based on performance parameters. For example, the Marine Performance Monitoring system developed by the Norwegian company KYMA has been applied in marine diesel engines, and has achieved satisfactory diagnostic performance [32]. The engine condition and diagnostic system produced by KONGSBERG monitors the fuel-injection and combustion processes persistently, and allows an expert system in the diagnostic system to detect engine faults remotely [33]. Fault diagnosis for marine diesel engines based on vibration signals started in the 1970s; presently, many advanced countries participating in the shipping industry have applied vibration signals for online condition monitoring in main engines. Specifically, using the vibration signals collected from an engine body, the pressure diagrams of the cylinders can be identified. Using a combination of the pressure diagrams and the instantaneous angular speed, the in-cylinder pressure variations can be calculated. Hu et al. designed a monitoring and diagnostic system for a marine diesel engine that integrated multiple methods and parameters. The system contained six sub-monitoring systems, including thermal parameter-monitoring systems, instantaneous speed-monitoring systems and cylinder pressure-monitoring systems [34].

Online oil monitoring has attracted significant attention in the field of tribology, owing to its outstanding application effects. Research on online oil monitoring has mainly focused on the design of online wear particle sensors and oil physicochemical sensors. Many companies have devoted efforts to the development of new sensors. In particular, the Gill sensor company invented a sensor for monitoring the volume of ferrograph wear particles, and a viscosity sensor company from Germany developed an 'AS-series' moisture sensor. Kittiwake (from the UK) developed an 'FG-series' online wear particle sensor, whereas MEAS (from America) proposed a new online viscosity sensor, the FPS2800B12C4 [35–39]. Many universities have also conducted relevant research. Specifically, Murali et al. designed a sensor for counting the number of wear particles at different sizes. This sensor was designed according to the principle that the capacitance changes when a particle passes through a sensor [40]. Hamilton et al. and Wu et al. developed online ferrographic sensors for monitoring the number of wear particles in lubricating oil, and further evaluated the wear conditions of mechanical equipment [41, 42]. Markova et al. and Heinisch et al. designed online viscosity sensors based on acoustic vibration signals and a magnetoelastic principle, respectively [43, 44]. Raadnui et al., Schullerh et al. and Moon et al. designed resistance-type viscosity sensors and capacitance-type viscosity sensors [45–47]. The Reliability Institute at the Wuhan University of Technology developed an online oil-monitoring system for the marine power system of an 8 000 m^3 drag-suction dredger, and the viscosity, moisture and abrasion losses were monitored online using the system [48].

2.2.2 Remote CMFD. Developments in the Internet and mobile communications have promoted the application of remote CMFDs. Wärtsilä established a condition-based maintenance (CBM) system for monitoring the mechanical, performance, and thermo-technical parameters of diesel engines. With the CBM system, technicians could monitor and analyse the technical parameters of engines to determine a full life-cycle maintenance plan, so that the normal operating time of the engines could be maximally prolonged [49]. The COSCO Group and Shanghai Maritime University developed a remote monitoring system for an engine room that used Inmarsat communication to realize information exchanges between the ship side and shore side. Inmarsat-C sent the parameters of the equipment in the engine room to the onshore company regularly for analysis, and engineers could control the ship inland according to the analysis results [50]. The Wuhan University of Technology built a ship remote fault-diagnostic system denoted IRDS V1.0 in February 1999; after 20 years of development, the system has developed into an intelligent remote CMFD system using 4G/5G/GPS/Big Dipper/high broadband/Inmarsat for remote data transmission, memory management, intelligent monitoring, emergency decision-making and maintenance management [51]. Chen designed a remote monitoring system for dredger machinery based on wireless networks. The system comprised an onboard monitoring system, ship-to-shore communication system and shore-based remote condition-monitoring system. In the system, general packet radio service messages and short messages were used to transmit data between ships and shores [52]. Li et al. acquired the instantaneous angular speed of a marine diesel engine using an online condition-monitoring system, and passed the data back to a data centre on land through compressed sensing technology. In the data centre, the instantaneous angular speed was uncompressed and processed to remotely diagnose combustion faults [53]. Yan et al. used an online oil condition-monitoring system to collect oil information, and sent the data to a shore-based maintenance centre and laboratories separately through a remote fault-diagnostic system. The wear characteristics were extracted from the oil information in the laboratories, and the wear states and wear modes were identified in the maintenance centre [54].

2.3 Third generation of CMFD

The third generation of CMFD has emerged based on developments in automation, artificial intelligence and big data, and focuses on intelligent fault-diagnosis methods. With multiple sources of information and data, the third-generation CMFD uses intelligent algorithms to imitate the inference processes of human beings, and to realize man/machine diagnoses. Consequently, engineers can evaluate the health conditions of marine power systems without overhauling, and can make appropriate and smart maintenance plans. At present, intelligent fault-diagnosis approaches for marine power systems include fault diagnoses based on quantitative models, data-driven fault diagnoses and fault diagnoses based on expert systems.

2.3.1 Fault diagnosis based on quantitative models. In quantitative fault-diagnostic models, accurate and reliable physical models and/or mathematical models are built, and faults are forecasted according to the deviations between the outputs given by the diagnostic models and observed values given by the sensors. Precise physical models of marine power systems can significantly influence the performance of the diagnostic models; therefore, Hountalas et al. and Kimmich et al. built physical models for the key systems of diesel engines, such as the intake, exhaust and fuel-injection systems. They found that fault-diagnostic models developed based on the above physical models could quickly identify incipient faults in the early stages [7, 55]. The fault-diagnostic methods based on quantitative models include the parametric estimation method, state-estimation method and parity-space method. In Ref. [56], the state equations were built for a rudder servo system (RSS) in a marine power system, according to the working principle of the RSS. By calculating the state deviations under different fault modes, the RSS faults were identified. Oleksiy et al. introduced a non-linear engine-dynamic model for capturing internal engine states, and an unscented Kalman filter for concurrently performing disturbance and state estimations [57]. Considering that the parameters of the diagnostic models vary significantly with the changes in engine working conditions, Han et al. proposed an enhanced intermittent unknown input Kalman filter for predicting the faults in a marine diesel engine. The diagnostic model performed well in a complicated working environment, and under varying working conditions [58]. As the parity space method is mostly applied in linear systems, it is not suitable for complex and non-linear marine power systems [59]. Quantitative models can accurately identify faults with the support of precise physical or mathematical models. However, an excessive number of characteristic parameters must be estimated for the physical or mathematical models; thus, the quantitative models are difficult to apply in fault diagnosis for marine power systems.

2.3.2 Data-driven fault diagnosis. With advancements in various data-mining technologies, data-driven fault-diagnostic models have been built to explore the information hidden in data, and to distinguish between the normal and fault states of marine power systems. Currently, this is a practical technique for fault diagnosis.

Fault diagnosis based on statistical analysis. Statistical analyses can be divided into univariate and multivariate statistical analyses. Generally, a univariate statistical analysis ignores the relevance among variables (i.e. fault features), and is therefore appropriate for diagnosing faults with small feature dimensions, such as in a statistical control process (SPC). Zhou et al. used an SPC to predict faults in marine diesel engines based on oil information [60]. Conversely, a multivariate statistical analysis is effective at describing the relevance among variables, and can therefore easily be applied for fault diagnosis with high feature dimensions. Principal component analysis (PCA) is the most widely used multivariate statistical method. Li et al. used PCA to extract principal components from vibration signals collected from a gearbox. With these principle components, the fault modes of the gearbox were identified [61]. To enhance the performance of PCA in nonlinear fault diagnosis, Wang et al. combined a kernel density estimation (KDE) with PCA, and used the KDE to estimate the probability density functions of Hotelling's T^2 and Q statistics. With this method, the incipient faults in a marine diesel engine were diagnosed [62]. A PCA assumes that data should obey a Gaussian distribution, but not all data from marine power systems can meet this demand. Independent component analysis (ICA) has been proposed to solve this problem. Loutas used an ICA to comprehensively extract independent components from vibration signals, acoustic emission signals and oil information, and then built a relationship between the independent components and fault modes of a gearbox [63]. Compared with PCA approaches, the information entropy retained the physical meanings of the fault features better. Gao used a minimum entropy deconvolution method to extract clear fault features from vibration signals, and used them accurately diagnose bearing faults in a diesel engine [64].

Fault diagnosis based on signal processing. When equipment is in a fault state, the features of the signals collected from the equipment will change correspondingly, such as the amplitude, phase position and frequency. By processing and analysing the signals, we can comprehensively evaluate the working conditions of the equipment. The signal-processing methods used in fault diagnosis include wavelet transforms, EMD and spectral analysis. Silva et al. proposed a method for extracting useful features in the wavelet domain, and applied this method to diagnose the faults of electric drives in an electric ship. The diagnostic results showed that the proposed method could enhance the accuracy of fault classification [65]. Notably, spurious signals can easily exist in a wavelet transform, as Fourier analysis has some limitations in processing non-linear and non-stationary signals. Moreover, signals with small amplitudes are easily filtered through a wavelet transform. To solve this problem, Bi et al. comprehensively used wavelet denoising and EMD to extract fault features from vibration signals, aiming to identify cylinder knocking in diesel engines [66]. Although EMD can be used to decompose any signal, it lacks the support of mathematical models; thus, there is some blindness when processing signals with EMD. In marine power systems, the signals generated by different faults generate different spectral characteristics. A spectrum analysis can determine the fault modes by comparing the results of a modal analysis with known spectra. Omar et al. used a power spectrum to process pressure signals acquired from the fuel-injection system of a diesel engine, and accurately evaluated the combustion efficiency of the engine based on features extracted from the pressure signals [67]. In practice, one signal-processing method is generally combined with other signal-processing methods, so as to generate a more accurate diagnostic result.

Fault diagnosis based on machine learning. Machine learning-based fault-diagnostic methods are more appropriate for establishing non-linear relationships between fault features and fault modes. Many machine learning algorithms have been successfully applied for fault diagnoses of marine power systems, such as artificial neural networks (ANNs) and support vector machines (SVMs). The back propagation ANN (BP-ANN), as a typical machine learning algorithm, has been widely applied to detect faults in marine diesel engines, such as faults in cylinders and wear faults [68–70]. However, the structure of the BP-ANN is difficult to determine, and the convergence rate is slow. To overcome these problems, ANNs with different hidden-layer functions have been applied in the fault diagnosis of marine diesel engines, including networks based on the radial basis function, probabilistic neural networks and fuzzy neural networks [71–73]. An ANN needs to be trained by a large number of training samples, so it may not perform well when the training data set is small. An SVM is superior for non-linear fault identification with small samples and high-dimensional features. In Refs. [74, 75], fault features were extracted from vibration signals and the instantaneous angular speed, respectively, and both studies developed SVM models for identifying common faults in marine diesel engines. Additionally, Zhu et al. proposed a fuzzy SVM for diagnosing the faults in a main engine in a ship power station [76]. Hu et al. proposed a multi-regression least-square SVM model for identifying concurrent faults in the cooling system of a main engine [77].

With advancements in the data-collection capacities of multi-source information-acquisition systems, the resultant massive amount of data has brought new opportunities and challenges to fault diagnosis. Deep learning is an effective method for big data analysis and mining. Zhang et al. used the vibration signals collected from a cylinder head as direct inputs to a convolutional neural network-based diagnostic model. The feature signals were processed through the convolutional layers, and then a misfire fault was diagnosed based on a multi-classification function [78]. Zhang et al. developed a long short-term memory network for identifying bearing degeneration, based on information reflecting the evolution of bearing faults. The model was optimized by using a particle filter algorithm to improve the diagnostic accuracy [79]. Deep learning has a strong representation learning ability, but also has problems in processing the associated data, missing data and imbalanced samples; these issues should be solved in the future.

Fault diagnosis based on information fusion. Generally, the information from a single sensor cannot reflect the overall working conditions of marine power systems. Information fusion can integrate multi-source information, so as to describe the states of marine power systems more comprehensively. Song et al. used the Dempster–Shafer (D-S) theory to fuse performance parameters collected by multiple sensors, and then used them to diagnose faults in a ship diesel engine [80]. Unlike D-S theory, an evidential reasoning (ER) rule clearly distinguishes between the reliability and importance of evidence [81]. Xu et al. comprehensively used two-dimensional and three-dimensional characteristics of wear particles to identify the wear modes of a marine diesel engine [82]. In practice, to improve the performance of fault-diagnostic models, the results given by several diagnostic models can be fused at the decision level. Xu et al. developed three wear fault-diagnostic models for marine diesel engines based on a belief rule-based (BRB) inference methodology, ER rule and BP-ANN. By considering the diagnostic accuracy and stability of every diagnostic model, a reliability factor was calculated for every model. Finally, the outputs of the three models were fused with an ER rule at the decision level, to generate a more robust diagnostic result [83].

2.3.3 Fault diagnosis based on expert systems. Expert domain knowledge is essential in fault diagnosis for marine power system due to the lack of high-quality fault data [84]. Current research on expert systems mainly focuses on system optimization and combinations with other algorithms. The fuzzy expert system is one of the

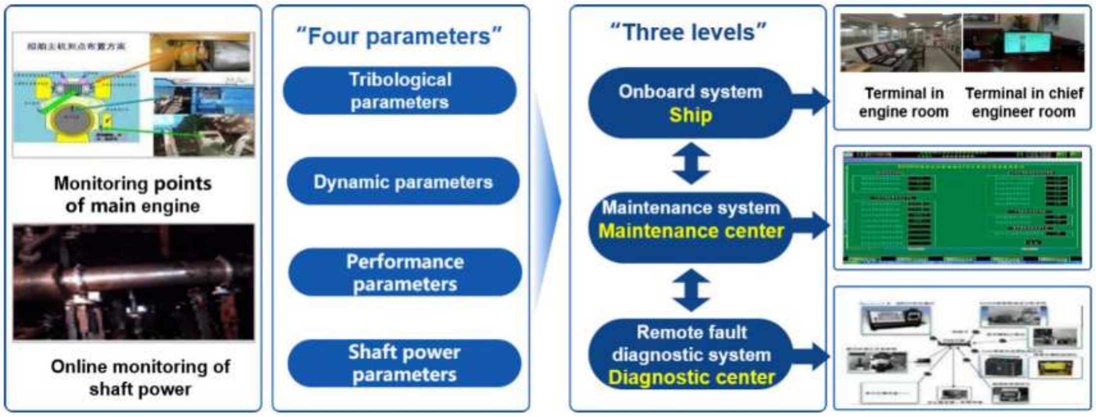

Fig. 2. CMFD platform for engineering ships

most widely applied expert systems. Tasdemir et al. used experimental data on engines and domain expert experience simultaneously to build a fuzzy expert system, which was applied to estimate and predict the power, torque and combustion performance of an engine [85]. Although a fuzzy expert system can process information uncertainty to a certain degree, its capability for learning and knowledge acquisition requires further enhancement. A BRB inference methodology can address different types of information uncertainties, such as ignorance, fuzzy information, incomplete information and probabilistic uncertainties [86]. BRB approaches have been successfully applied in the fault diagnoses of marine power systems. Considering that the materials of each wear part in a diesel engine were different, Xu used the contents of the different elements in the lubricating oil as fault features, and proposed a diagnostic model in a parallel structure for locating the wear parts in a diesel engine. The diagnostic model comprised several sub-BRB systems corresponding to the key wear parts of the engine. More importantly, the model was appropriate for concurrent fault diagnosis [87]. In Ref. [88], a bi-level BRB model was established to identify the wear modes of a diesel engine step by step, simultaneously increasing the diagnostic accuracy and reducing the model complexity. Additionally, BRB is also combined with other algorithms, such as Bayesian network, to improve the diagnostic accuracy with high uncertain data [89].

In third-generation CMFD, in addition to the above intelligent diagnostic methods, a patrol robot is another potential approach that should be further applied in CMFD for marine power systems. A patrol robot synthesizes robotics, automatic control and image processing to realize intelligent patrols for key equipment in marine power systems, regardless of whether it is in a conventional or dangerous environment. It can also help evaluate the operating conditions of marine power systems and identify faults. The patrol robot is a further expansion of IntelliSense. It will play an important role in the construction of an unmanned engine room, and will promote the further development of smart ships.

3. Application cases of CMFD in marine power systems

Since the 1980s, Wuhan University of Technology has conducted research on CMFD for marine power systems. They have developed several CMFD systems for various ships, including dredgers, salvage ships, container ships and a solar photovoltaic ro-ro ship.

3.1 CMFD platform for dredgers

The equipment in dredgers generally operates in harsh environments, and wear faults can easily occur. Considering the operating characteristics of dredgers, an innovative philosophy was proposed regarding the management of the machinery in dredgers, involving remote wireless condition monitoring, fault diagnosis and maintenance. Different types of dredgers were selected as application objects; most of them belonged to the Changjiang Waterway Bureau. A modularized and distributed machinery management platform was developed, and provided functions for remote monitoring, fault diagnosis, machinery management and maintenance-decision support. As shown in Fig. 2, the CMFD platform covered ships, inshore diagnostic centres and inshore maintenance centres [12].

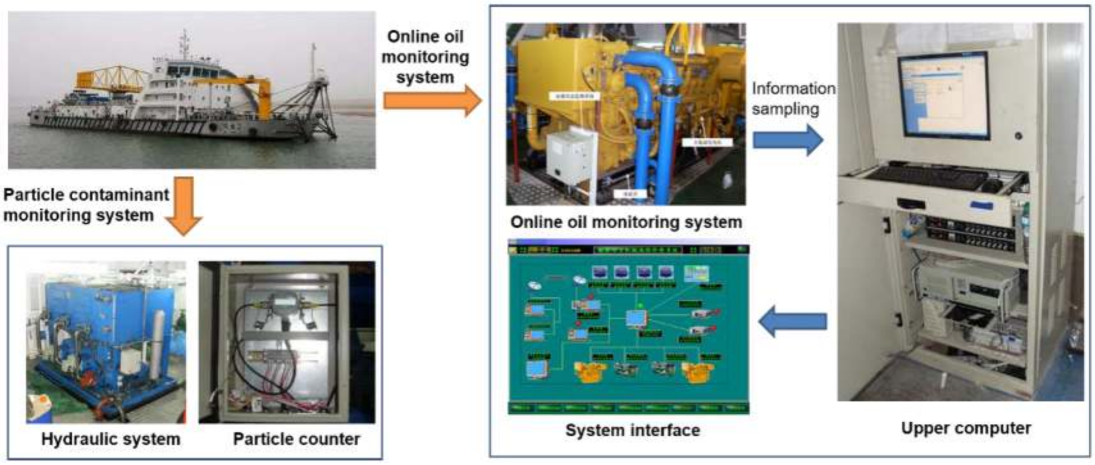

Fig. 3. CMFD platform on the dredger Xipan 2

The remote platform mainly monitored the key electromechanical equipment (such as diesel engines and electric generators), key dredging equipment (such as dredge pumps and gearboxes) and hydraulic systems. The platform fused instantaneous angular speed, performance parameters, vibration signals and oil information to detect faults and predict the health states of dredgers. The dredger, maintenance centre and diagnostic centre communicated with each other through remote wireless communication. By analysing the maintenance data of the equipment in the dredgers, a network-based database, model base and knowledge base were built. Visual Basic was used as the software platform for developing a remote maintenance-decision tool; this software was able to determine maintenance modes, make maintenance plans, optimize maintenance-process routes and support emergency maintenance.

The CMFD platform was successfully applied in several dredgers, such as the Hangjun 20, the Changjing 2 and the Xipan 2. Taking the Xipan 2 as an example, the CMFD platform for the dredger is shown in Fig. 3. The CMFD platform could detect abnormal states of the main engine and hydraulic system, and then could send alarms to engineers on board. Meanwhile, with the intelligent diagnostic models integrated into the platform, the potential wear faults in the marine power system could be diagnosed. The online oil-monitoring system of the CMFD platform on the Xipan 2 contained an online ferrographic sensor, an online viscosity sensor and a moisture sensor, by which the wear particle content and particle images were acquired. With the particle content and particle images, a system was built incorporating wear-state monitoring, wear fault-feature extraction and wear-trend prediction [90]. Additionally, a particle contaminant-monitoring system in the CMFD platform monitored and evaluated the degree of contamination of the hydraulic oil. Specifically, the particle counter calculated the number of particles with sizes $> 4\ \mu m$, $> 6\ \mu m$, $> 14\ \mu m$ and $> 21\ \mu m$. Based on the correspondence between the number of particles and International Standards Organization cleanness codes, the contaminant degree could be determined [91]. Based on the evaluation results, severely polluted hydraulic oil was able to be replaced in time, enhancing the service lives of the hydraulic components. Meanwhile, the oil information acquired on board was sent to the diagnostic and maintenance centres through the wireless network. In these centres, the data was used to study the fault mechanisms, and to develop more accurate diagnostic models.

With the use of CMFD platforms, the failure frequency and mean time to repair are both reduced. Compared with a dredger without the CMFD platform, the working hours per month of the dredger with the CMFD platform increase by 3.4%, and the maintenance cost is reduced by 5%. The public service capability of dredgers is improved with CMFD platforms; this is significant for the maintenance of the Yangtze River waterway.

3.2 CMFD platform for salvage ships

Salvage ships are the most reliable safeguards for human lives and property security. A team from Wuhan University of Technology installed an

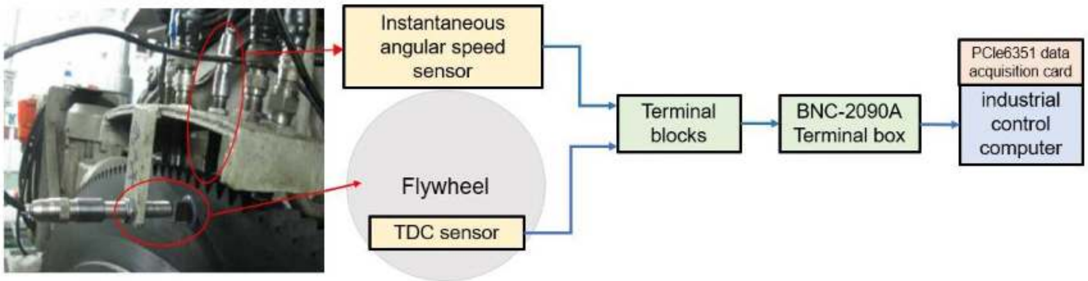

Fig. 4. Positions of sensor installation and measurement principle for instantaneous angular speed

online CMFD platform on several ocean salvage ships. The CMFD platform monitored the conditions of the main engine, auxiliary engine, gearbox and hydraulic system. The platform comprised monitoring modules for performance parameters, such as the instantaneous angular speed, vibration, lubricating oil, particle contaminants and telecommunication. Among these modules, the module for the instantaneous angular speed is an essential part of the CMFD platform, as it can monitor the combustion states in cylinders. In addition, it can be used to rapidly diagnose combustion faults [92].

A magneto-electric sensor was used to collect the instantaneous angular speed signals. Fig. 4 shows the installation positions of the sensors and the measurement principle for the instantaneous angular speed. As shown in Fig. 3, a TDC sensor was installed on the wedge opposite to the head face of an engine flywheel, and the instantaneous angular speed sensor was installed above the flywheel. The signals collected by the two sensors were transformed from analogue signals to digital signals by a data-acquisition card, and were stored in an industrial control computer for further analysis. Wang illustrated how to filter noise and extract features from the instantaneous angular speed based on EMD and variational mode decomposition methods [93]. Based on a multi-harmonic phase theory, combustion faults such as misfires, uneven power and abnormal fuel-supply advance angles could be identified by comparing the amplitudes and phase positions of the instantaneous angular speed in different harmonic phases [94].

Salvage ships are regarded as aquatic fire stations, and are used to save lives. CMFD platforms ensure the safe and reliable operation of salvage ships, so that the ships can work efficiently. CMFD platforms have been applied in many of the salvage ships affiliated with China Rescue and Salvage. These salvage ships have rescued thousands of lives and ships, along with safeguarding personal safety and property.

3.3 CMFD platform for screw shafts in container ships

CMFD systems for marine power systems have been applied in the 13500TEU and 21000TEU container ships of the COSCO Shipping Group. Based on the platform, the condition of the stern bearing oil is monitored online, and time series are acquired reflecting the physicochemical properties of the lubricating oil and content of the wear particles. All online monitoring data are centrally managed on board, and can be accessed and processed remotely through satellite data transmission. Fig. 5 shows the stern bearing in a real container ship, and an online monitoring device for the stern bearing oil. The online motoring system comprises an electromagnetic induction wear particle counter, viscosity sensor, moisture sensor and electromagnetic oil pump. The device collects oil samples from an oil circuit in the stern bearing, and the oil samples return to the oil circuit again after being tested by the sensors in the device. With this device, various indicators reflecting the lubricating oil condition can be monitored in real time.

Based on this online condition-monitoring device, a dynamic mesh finite-element model was built to describe the film of the stern bearing oil and the movement of the wear particles in the oil film. The finite-element model could calculate the content of the wear particles in the oil-return pipe, so that the distribution of wear particles in the stern bearing could be inferred based on the monitoring information. Through the finite-element model, the moving trajectories and dynamic distributions of the wear particles in the oil films of the stern bearing under different rotating speeds and oil film loads were determined. Consequently,

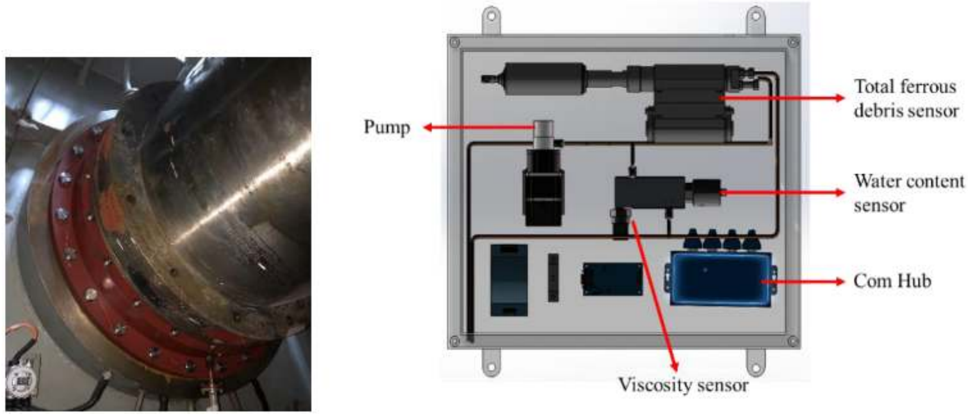

Fig. 5. Stern bearing in a real container ship and online oil-monitoring device

the shafting dynamic model was coupled with the lubrication model to explore the mapping relationships between the monitoring parameters (such as bearing bush temperature, vibration, film thickness and wear-particle content) and the abnormal wear modes of the stern bearing. All of these relationships constituted the knowledge base for fault diagnosis. Fig. 6 describes the detailed diagnostic- and model-calculation processes. Currently, the CMFD platform is being used by a shipping company to develop a smart cabin system for a container ship, generating a profit of over 3.2 million RMB.

3.4 CMFD platform for solar photovoltaic ro-ro ships

To ensure the reliability of the solar photovoltaic system in a large ro-ro ship named 'COSCO Tengfei', a CMFD platform for the solar photovoltaic system was developed, as illustrated in Fig. 7 [95]. The platform collected the data of every module in the solar photovoltaic system in real time, including environmental parameters, photovoltaic controller data, battery data, grid/off-grid inverter data and power-distribution cabinet data. The platform monitored the operating conditions of the photovoltaic system, and displayed alarms when the system was in an abnormal state. Under these circumstances, the control equipment was activated, and took protective actions. Through the 3G network, a data communication interface was built between the CMFD platform and land-based Internet. Moreover, a browser/server (B/S) structure based on web technology was established, and the engineers in the shore-based data centre could remotely watch the operating conditions of the solar photovoltaic system through the web explorer in real time. In the platform, a FrameView operation station was used as the human–machine interface in the upper computers. The upper computers could display, store and process data through the interface. The data stored in the upper computers was analysed to simulate the processes of solar power generation in large ocean ships, and to evaluate the factors influencing power generation. These studies, based on historical data, have helped promote the development of solar ships.

The software for the CMFD platform contained modules for data input, data processing and data output. Fig. 8 illustrates the design process of the software. The software read data from the solar charger controller, battery-management system, inverter and monitoring system of the ship power station, respectively, using the RS 485 protocol. The data included the voltage and current of the photovoltaic batteries, voltage and current output by the inverter, inverter frequency, inverter power, and inversion efficiency. Once the platform received the fault data, the solar controller, inverter, battery-management system and ship power station automatically took protective actions, and the platform generated alarms. The fault messages were sent to the remote terminals via satellite communication, and then the terminals informed the engineers to handle the fault in sufficient time. The software also stored the real-time parameters of the solar photovoltaic system and periodically cleared the historical data, making it convenient for historical data queries.

The solar photovoltaic system in 'COSCO Tengfei' was equal to a 143 kW solar generator, and could work normally with the CMFD system. Assuming that the photovoltaic system worked 16 h every day with sufficient sunlight, the ship could save 0.46 t of fuel oil; this is quite meaningful for energy conservation and emissions reduction in the shipping industry.

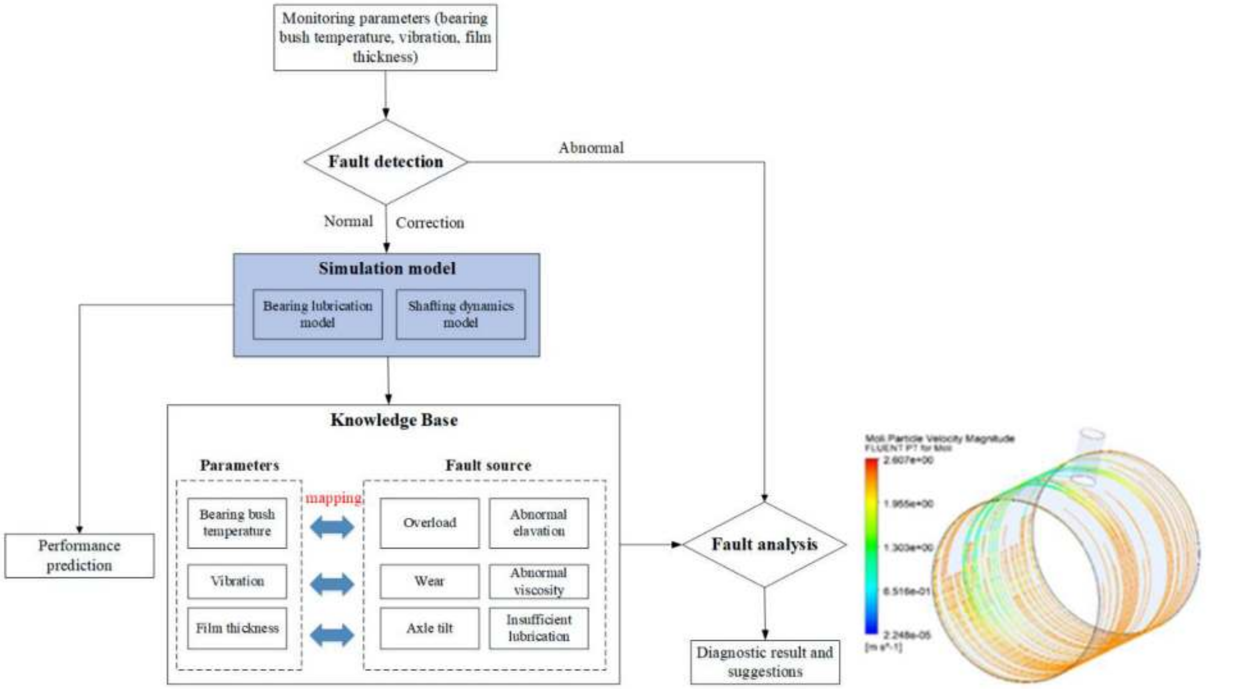

Fig. 6. Fault diagnostic process and model calculation for stern bearing

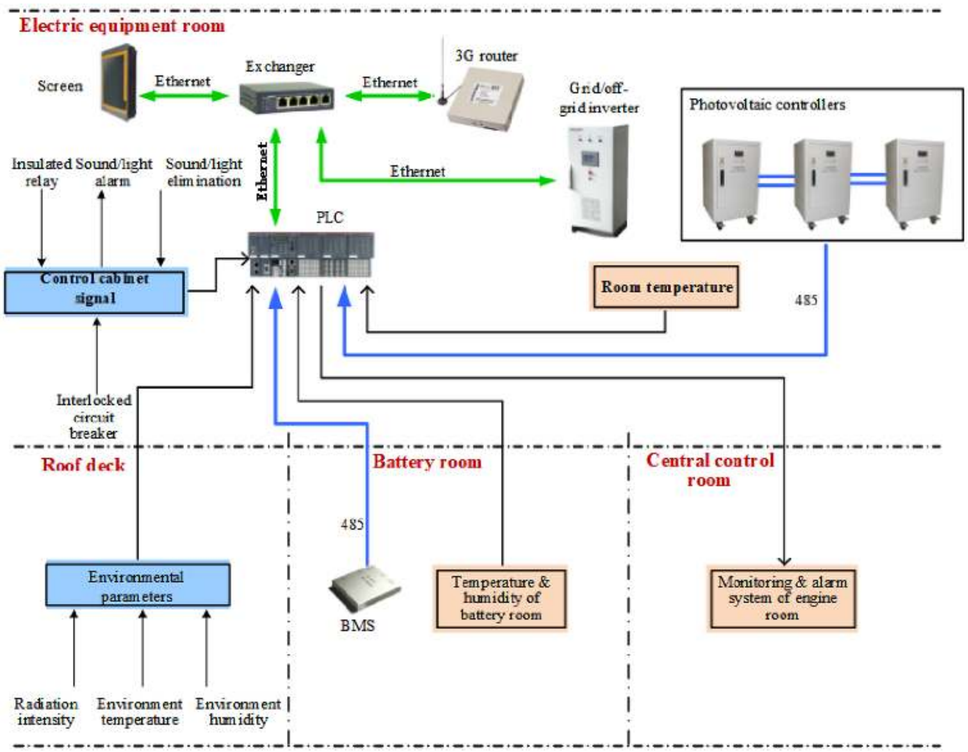

Fig. 7. Structure of the CMFD platform for the solar photovoltaic system in the ro-ro ship

4. Research trends and challenges

Nowadays, ships are developing toward green and low-carbon approaches. Simultaneously, advanced technologies such as artificial intelligence, cloud computing, the Internet of Things (IoT) and big data have promoted the development of smart ships. With this background, the

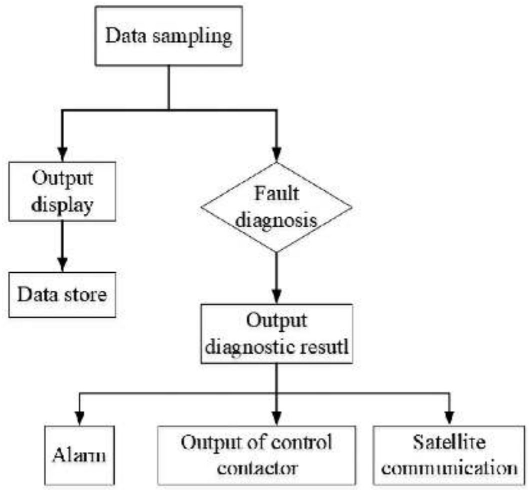

Fig. 8. Design process of the CMFD software for the solar photovoltaic system

CMFD for marine power systems is expected to develop in the following directions.

4.1 Development of remote shore-based driving and control technologies for ships, and building of ship-control centres on land

We should develop shore-based control centres for ships, and combine them with autonomous navigation systems and intelligent robots on board to create a 'shore-based driving and control + ship-side attending' navigation mode. With the new navigation mode, the number of crew on board can be reduced, and the navigation security can be improved. In the future, the engine control room on board will switch to a shore-based engine-control centre (ECC). The ECC will be an important part of the CMFD for marine equipment, and will strengthen the collaboration between ships and control centres on land, so that shipping enterprises can control their entire fleets remotely. Remote fault diagnosis for ships will be conducted based on cloud computing. Based on cyber-physical systems, the remote fault-diagnostic system will sample, store, analyse and mine the big data collected from ships, and make decisions and predictions based thereon. Furthermore, we should take full advantage of ship-borne systems and shore-based control centres to study a vessel–shore integrated maintenance mode, including vessel–shore integrated maintenance resource planning, dynamic scheduling, supply and distribution. Notably, however, there are some challenges in the construction of shore-based centres. First, the staff in shore-based centres should have a real perception of the situation at sea to manipulate ships in a reliable and safe way. Therefore, we must further understand the human factors influencing remote condition monitoring and ship handling. In addition, smart sensing technologies, digital modelling technologies and integrated modelling technologies must be further developed. Then, driving and controlling ships from the shore can propose higher demands for crew quality. The crews should master essential skills, including those concerning information sensing, communication, navigation and remote control, and should expand their knowledge regarding operating and maintaining intelligent systems in shore-based centres.

4.2 Developing monitoring and security technologies for new energy ships

Nowadays, new energy ships such as solar, fuel cell and hybrid ships are being more widely used. Compared with traditional fossil fuel energy-powered ships, new energy ships are more complicated and have more hidden safety hazards, such as leakages of hydrogen and thermal runaways of lithium batteries. Consequently, the CMFD platform should be built for new energy ships based on multiple analysis methods. For example, the CMFD platform should comprise a marine IoT platform and a big data platform, along with the technical frameworks for the application of these platforms. In the construction of CMFD platforms for new energy ships, an IoT protocol should be established while considering the characteristics of the ships. The compatibility and expansibility of the data format and content should be considered in the IoT protocol. Based on the CMFD platform, intelligent fault-diagnostic models should also be built for identifying the fault states of key equipment in new energy ships, and for locating faulty components. Moreover, the fault trends should be predicted using diagnostic models. As ships powered by different new energies have their own characteristics, developing an appropriate CMFD system for a specific type of new energy ship is a significant challenge affecting ship security. For example, in liquid natural gas (LNG) ships, methane sensors, smoke sensors and optical sensors should be installed in the LNG tanks and pipe connections in the fuel-supply systems. All of these sensors can monitor the condition of the engine room, so as to avoid fire accidents. In solar energy-powered ships, the energy systems are dispersed. Therefore, determining how to manage these energy systems centrally and how to monitor photovoltaic power stations in real time are particularly important for ensuring ship safety.

4.3 Combining energy-efficiency control for marine power systems with CMFD techniques

To promote and optimize energy efficiency in ships, researchers should study dynamic modelling for the navigation environment and ship energy efficiency, energy-efficiency monitoring and evaluation, adaptive control of energy efficiency and loading optimization. Specifically, by analysing the characteristics of the navigation environment, ship-energy consumption, and navigation speeds in different segments and seasons, a dynamic response relationship can be built between the navigation environments and ship propulsive loads. We should study how to monitor the fuel consumption, gas consumption, electric consumption, power, rotating speed, speed relative to water, speed relative to land and other features used in energy-efficiency management. Monitoring data regarding energy efficiency should be preprocessed using machine learning methods. With the features extracted from the data, an evaluation model for the ship's energy efficiency should be developed to identify the sailing conditions of ships and evaluate the energy efficiency. Based on the evaluation results, the relationship between the accumulated energy consumption and rotating speed can be studied, and a speed-optimization model can be established to realize self-adaptive control of the energy efficiency in ships. Based on the results from the speed optimization and taking the navigation environment as the constraints, we can explore how the speed and loading affect the energy efficiency of the ships. Currently, most studies on ship energy-efficiency control focus on data acquisition; however, analysing and mining the data to explore the information hidden behind the data is the foundation for evaluating and predicting energy efficiency. Thus, in-depth studies on intelligent modelling approaches and intelligent optimization algorithms will be the keys to combining energy efficiency control with CMFD.

4.4 Combining ship-motion control with CMFD techniques

Presently, ship propellers are changing from traditional propellers to shaft-less rim-driven thrusters, as the new thrusters can decrease the power loss in the energy-transfer process, increase the energy-transfer efficiency and cargo dead weight, and reduce the manufacturing difficulty and cost. To promote the application of shaft-less rim-driven thrusters in practice, in addition to the technical issues of the shaft-less thrusters themselves, establishing an appropriate condition-monitoring system for the thrusters is another key challenge. A shaft-less rim-driven thruster has a tight structure, and every part is produced with high precision. Meanwhile, the thruster operates in a harsh environment with high salinity. To ensure the safe and reliable operation of shaft-less rim-driven thrusters, control methods and CMFD systems should be developed. The CMFD platforms should monitor the condition of the thrusters without damaging or disturbing the performance of the thrusters. Currently, most permanent magnet synchronous motors (PMSMs) in shaft-less rim-driven thrusters use position-sensor-less control; however, when the thruster operates at a low speed or starts frequently, it is difficult to control the PMSM using the position-sensor-less method. Therefore, we should explore high-resolution online measurement methods for measuring the rotor angular velocity, so that the PMSM rotating speed can be precisely controlled. This research is extremely significant for improving the speed-regulation performance of PMSMs. At the same time, intelligent cooperative control for multiple shaft-less rim-driven thrusters should be studied to enhance the manoeuvrability of ships. With regard to CMFD, we should develop new vibration-monitoring methods to collect the structural vibration signals of thrusters. The vibration is generally generated by the abnormal wear of water-lubricated bearings, and the unsteady pulsating force of the propeller. With the new monitoring methods, faults in key components in the thrusters can be diagnosed, which is essential to ensuring the safety and reliability of shaft-less rim-driven thrusters.

5. Conclusions

In this study, we summarized the developments in CMFD for marine power systems. Various techniques, models and algorithms were reviewed, based on the three periods of CMFD. The CMFD systems applied on several typical ships were illustrated in detail. These ships included dredgers, salvages, container ships and solar photovoltaic radio ships.

Although advanced CMFD techniques are available in the literature, there are still several difficulties affecting their implementation in practice. The difficulties include: (i) only a small amount of data is highly qualified to be used for developing the CMFD models directly, owing to incorrect data-collection approaches or faulty data collectors; (ii) the CMFD for the marine power systems is ignored in the design phase of ships, such that the essential interfaces for CMFD systems are not reserved, or such that many additional sensors have to be installed to meet the demands of the CMFD systems; (iii) theoretical research on CMFD is divorced from practice (e.g. the speed of some feature extraction methods or diagnostic algorithms cannot meet actual application demands); and (iv) with new energies and new propellers being applied on ships, the monitoring requirements, implementation plans and standards of CMFD must be modified.

The CMFD for the next generation of marine power systems will focus more on how to serve new energy ships and smart ships. We believe that the CMFD will develop in the directions proposed in Section 4. Meanwhile, additional attention should be paid to data acquisition, monitorability design, and close combinations of CMFD theories and applications, so as to ensure that the CMFD systems for marine power systems can play a role in the maintenance of ships.

Supplementary data

Supplementary data is available at *Transportation Safety and Environment* online.

Acknowledgements

We acknowledge financial support from the NSFC-Zhejiang Joint Fund for the Integration of Industrialization and Informatization (grant no. U1709215), the NSFC (grant nos 52071241, 61903108) and the Natural Science Foundation of Zhejiang Province (grant no. LY21F030011).

Conflict of interest statement

None declared.

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