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Condition Monitoring and Fault Diagnosis of Electric Propulsion Systems in Marine Transportation

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ABSTRACT

Electric propulsion systems (EPS) are increasingly being adopted in marine industry due to their efficiency, lower greenhouse gas emissions, and operational flexibility. However, harsh marine environment and continuous operation necessitate robust condition monitoring (CM) and fault diagnosis (FD) techniques to ensure reliability and prevent catastrophic failures. Continuous monitoring detects early signs of equipment degradation, preventing unexpected failures and ensuring uninterrupted operation of electric propulsion systems. Real-time monitoring prevents hazardous conditions such as overheating, insulation breakdown, or mechanical failures, enhancing crew and vessel safety. FD techniques identify inefficiencies in motors, power electronics, and energy storage, ensuring optimal performance and reduced energy consumption. CM and FD enable condition-based maintenance, reducing unnecessary scheduled downtime and allowing repairs only when needed, optimizing operational efficiency. Therefore, this paper presents a comprehensive review of CM and FD techniques specifically developed for marine EPS, addressing both conventional approaches and cutting-edge intelligent methods. It systematically examines vibration analysis, thermal monitoring, electrical signature analysis, and lubrication monitoring as foundational CM techniques, while exploring artificial intelligence, machine learning, and digital twin technologies in fault prediction and system health management.

1. Introduction

Marine industry is undergoing a significant transformation as it shifts toward electric propulsion systems (EPS) to meet environmental regulations and improve operational efficiency [1]. Traditional mechanical propulsion systems, which rely on internal combustion engines, are being replaced by EPS due to their superior fuel efficiency, lower emissions, and enhanced maneuverability. Electric propulsion systems contribute strongly to global sustainability targets. Transition from fossil-fuel propulsion aligns with international maritime regulations aimed at reducing carbon dioxide, sulfur oxides, and nitrogen oxides. Energy efficiency improvements directly impact operational expenditures, cutting fuel costs and extending component life. Beyond emissions reduction, quiet operation enhances environmental performance by lowering underwater noise pollution, protecting marine ecosystems. Research has demonstrated that hybrid and fully electric vessels generate up to forty percent less greenhouse gas compared to conventional counterparts. Ongoing innovation ensures gradual alignment with IMO 2050 decarbonization goals. Strong policy support will accelerate adoption across commercial and naval fleets, creating an essential foundation for sustainable maritime transport. Harsh marine environment, characterized by saltwater exposure, humidity, and temperature fluctuations, accelerates component degradation and increases failures in electrical and mechanical components [2]. International Maritime Organization and regional authorities increasingly mandate strict compliance with environmental and safety standards. Propulsion systems equipped with advanced condition monitoring help operators demonstrate adherence to emission caps, fuel efficiency indices, and safety frameworks.

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Continuous monitoring records act as verifiable compliance evidence during inspections. Regulatory incentives, such as subsidies or reduced port fees for low-emission vessels, encourage adoption. Conversely, penalties for non-compliance create financial risks for operators relying on outdated systems. Industry trend indicates growing alignment between technology adoption and regulatory compliance. Proactive monitoring strategies therefore represent not only engineering best practice but also economic necessity. Unlike conventional systems, EPS requires sophisticated condition monitoring (CM) and fault diagnosis (FD) techniques to ensure uninterrupted operation [3]. Unplanned failures can lead to costly downtime, safety hazards, and increased maintenance expenses, making proactive monitoring essential.

Condition monitoring and fault diagnosis play a critical role in maintaining both reliability and performance of marine EPS [3]. In electric propulsion drive trains, early detection of faults such as bearing wear, insulation degradation, or power electronics failures, prevents catastrophic damages and extends their lifespan. Traditional CM methods, including vibration analysis, thermal monitoring, and electrical signature analysis, have been widely used but face limitations in real-time applications. Recent advancements in artificial intelligence (AI) [4] and machine learning (ML) [5] have revolutionized fault diagnosis by enabling automated pattern recognition and predictive maintenance. For instance, motor current signature analysis (MCSA) combined with deep learning algorithms can accurately detect rotor bar defects in electric motors [6]. Despite these innovations, challenges such as sensor reliability in harsh conditions, data integration, and false alarms remain significant hurdles. This paper examines these challenges and presents case studies demonstrating successful implementations of CM and FD in marine EPS.

Future of condition monitoring in marine EPS lies in integration of emerging technologies such as digital twins, edge computing, and IoT-enabled predictive maintenance [7-9]. Digital twins, which create virtual replicas of physical systems, allow for real-time simulation and fault prediction, reducing any need for physical inspections [10]. Edge computing enables onboard processing of sensor data, facilitating immediate decision-making without relying on cloud-based systems [11]. Additionally, adoption of hybrid diagnostic methods, combining model-based and data-driven techniques, improves accuracy and reduces false positives. Development of robust and adaptive CM systems will be crucial for ensuring both reliability and safety of EPS.

Many existing reviews and studies tend to discuss CM/FD methods (e.g., vibration analysis, MCSA, AI) in isolation, without providing a critical, comparative framework for selecting a right method for a specific subsystem (e.g., motor vs. power converter vs. battery). There is a significant gap in critically evaluating these technologies specifically for the harsh marine environment. Existing works often understates challenges like sensor degradation from salt spray, data corruption from electromagnetic interference, and practical difficulties of implementing complex algorithms on vessels with limited computing resources. While new technologies like AI and Digital Twins are frequently mentioned, there is a lack of discussion on practical pathways for integrating these advanced methods with conventional techniques into a unified, cost-effective health management system for marine applications.

This paper introduces a novel, critical framework for evaluating and selecting CM/FD techniques based on specific subsystem (electric motor, power electronics, battery, propulsion mechanics) and its associated failure modes. A forward-looking synthesis on integration of conventional and intelligent methods is presented. It critically analyzes how AI and machine learning can augment traditional vibration and electrical analysis, and how Digital Twins can serve as a unifying platform for data fusion, moving discussions from theory towards practical implementation. Conclusion doesn't just list future trends but synthesizes them into a coherent vision (merging AI, digital twins, advanced sensing) and points to specific emerging research areas like optical fiber sensors, quantum sensing, and blockchain for data security in maritime CM, thereby guiding future research directions.

Hence, condition monitoring (CM) and fault diagnosis (FD) methodologies are introduced and investigated for electric propulsion systems (EPS) of marine transportation. Firstly, electric propulsion system architecture in marine applications is introduced in Section 2. Then, CM and FD techniques are discussed in Section 3. Finally, challenges and future trends are stated in Section 4.

2.Electric propulsion drive trains in marine industry

Electric propulsion systems are increasingly being adopted in marine applications due to their efficiency, flexibility, and environmental benefits compared to traditional mechanical propulsion [12]. Their architecture varies depending on vessel type, power requirements, and operational needs. As shown in Fig. 1, a typical electric propulsion system in marine applications consists of following major components [13]:

– **Power generation sources**
- Main generators (diesel/gas turbines, fuel cells, or hybrid systems): Provide primary electrical power.
- Energy storage systems (batteries, supercapacitors): Used in hybrid/electric vessels for load balancing and peak shaving.
- Shore power connection: For charging batteries or powering systems while docked.
- Renewable energy sources (solar, wind): Auxiliary power in hybrid vessels.

– **Power distribution and conversion**
- Switchboards and circuit breakers: Distribute power across system.
- Transformers: Adjust voltage levels for different loads.

- Frequency converters (AC/AC or DC/DC): Ensure compatibility between power sources and propulsion motors.
- DC/AC Inverters: Convert stored DC power (batteries) to AC for propulsion.

– **Propulsion drives and motors**

- Electric motors (synchronous or induction): Drive the propellers (azimuth thrusters, podded propulsors, or traditional shaft lines).
- Variable frequency drives (VFDs): Control motor speed and torque for optimal efficiency.
- Propulsion control system (PCS): Manages motor operation based on navigation demands.

– **Energy management and control systems**

- Power management system (PMS): Optimizes power generation and distribution.
- Energy storage management system (ESMS): Controls battery/supercapacitor usage.
- Integrated automation system (IAS): Monitors and controls all electrical and propulsion components.

Different vessel types use varying electric propulsion configurations:

– **Diesel-Electric Propulsion**

- Description: Diesel generators supply power to electric motors driving propellers.
- Advantages:
  - Better fuel efficiency at variable speeds.
  - Flexible engine placement (no direct shaft connection).
  - Reduced maintenance compared to mechanical systems.
- Applications: Cruise ships, ferries, icebreakers, naval vessels.

– **Hybrid-electric propulsion**

- Description: Combines diesel generators with batteries/supercapacitors.
- Modes of operation:
  - Full electric mode (Zero emissions in port/sensitive areas).
  - Hybrid mode (Optimal fuel efficiency by load-sharing).
  - Diesel-only mode (High-power demands).
- Applications: Tugs, offshore supply vessels, short-sea shipping.

– **Full battery-electric propulsion**

- Description: Relies entirely on battery power (charged from shore or renewables).
- Advantages: Zero emissions, quiet operation.
- Challenges: Limited range, high battery weight/cost.
- Applications: Small ferries, harbor vessels, inland waterway ships.

– **Fuel cell electric propulsion**

- Description: Uses hydrogen fuel cells to generate electricity for propulsion.

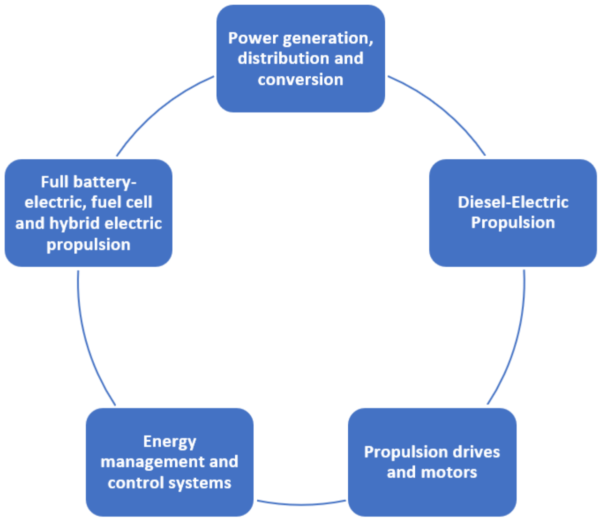

Fig. 1. Main components of EPS in marine transportation systems

- Advantages: Zero emissions (only water as byproduct), high efficiency.
- Challenges: High cost, hydrogen storage/refueling infrastructure.
- Applications: Future-proof designs for ferries, research vessels.

Integration complexity remains a key challenge for marine EPS. Combining diverse power sources, storage systems, and dynamic loads into one cohesive network demands sophisticated control strategies. Power management systems must balance generator output with battery state-of-charge while meeting sudden thrust demands. This requires real-time optimization algorithms to ensure fuel efficiency and system stability. Furthermore, harmonic distortions from multiple power converters can affect power quality, potentially leading to interference with navigation and communication systems. Employing active filtering and advanced converter topologies becomes essential for maintaining a clean electrical network onboard a vessel, safeguarding both propulsion and auxiliary systems from electrical noise and voltage fluctuations.

Redundancy is a critical design factor for marine EPS, particularly for vessels operating in open seas or polar regions. A single point of failure could lead to total propulsion loss, creating hazardous situations. Therefore, systems often incorporate redundant generators, split switchboards, and multiple independent motor drives. Power distribution networks are designed with ring mains or duplicate busbars to isolate faults and maintain power supply to vital loads.

This architectural complexity, while enhancing reliability, also increases a number of components requiring monitoring. Consequently, a robust CM strategy must cover not only primary machinery but also backup systems and interconnection points to ensure fail-safe operation under all conditions. Table 1 presents a comparison between various types of marine propulsion drive trains [14].

3. CM and FD Methods of Electric Propulsion Systems

Electric propulsion systems are increasingly adopted in marine industry due to their efficiency, reduced emissions, and operational flexibility. However, their complex electromechanical nature makes them susceptible to various faults that can lead to costly downtime. Effective CM and FD are critical for ensuring reliability, optimizing maintenance, and preventing catastrophic failures.

Figure 2 visually illustrates a schematic integration of conventional CM techniques (vibration, thermal monitoring, MCSA) with intelligent layers (AI/ML, model-based diagnosis, and digital twins), highlighting data flow, decision layers, and maintenance outputs. According to Table 2, marine electric propulsion systems consist of several critical subsystems, each prone to specific failure modes:

- **Electric motors:** Stator winding faults, rotor bar fractures, bearing wear, and cooling system failures.
- **Power electronics:** IGBT/MOSFET failures, capacitor degradation, gate driver faults, and thermal overstress.
- **Energy storage systems:** Battery cell imbalance, capacity fade, thermal runaway, and connection faults.
- **Propulsion mechanics:** Thrust bearing wear, shaft misalignment, seal leakage, and propeller cavitation.

Early detection of these faults through condition monitoring prevents unexpected breakdowns and extends system lifespan. A comparative analysis of different CM and FD methods for marine electric propulsion systems is provided in Table 3 [15, 16].

Selecting appropriate sensors is a foundational step in building an effective CM system. Sensors must withstand harsh marine conditions, including constant vibration, humidity, salt spray, and wide temperature swings. For vibration analysis, industrial-grade accelerometers with robust housing and high ingress protection (IP) ratings are mandatory. Current transformers for MCSA need high accuracy across a wide frequency band to capture harmonic content.

Thermal sensors, whether infrared cameras or embedded thermocouples, require calibration to account for ambient conditions. Furthermore, sensor placement is critical; for instance, accelerometers must be mounted directly on bearing housings to capture high-frequency signals, and current sensors must be placed on correct phases. Redundant sensor placement on critical components can enhance data reliability and provide fault tolerance for monitoring system itself.

Data acquisition and preprocessing form the backbone of any diagnostic pipeline. Raw sensor data is often noisy, especially in an electromagnetically noisy environment like a ship's engine room. Signal conditioning—including amplification, filtering, and analog-to-digital conversion—must be performed with high fidelity. Anti-aliasing filters are essential before sampling to prevent false frequency interpretations.

Table 1. Comparison of marine propulsion system types

Propulsion Type	Key Power Sources	Emissions Profile	Operational Flexibility	Ideal Vessel Types
Diesel-Electric	Diesel Generators	Medium	High	Cruise Ships, Icebreakers, Naval
Hybrid-Electric	Diesel Gensets + Batteries	Low to Zero (mode-dependent)	Very High	Tugs, Offshore Supply, Short-sea
Full Battery-Electric	Batteries	Zero (at point of use)	Moderate	Ferries, Harbor Vessels
Fuel Cell Electric	Hydrogen Fuel Cells	Zero	High	Ferries, Research Vessels (Future)

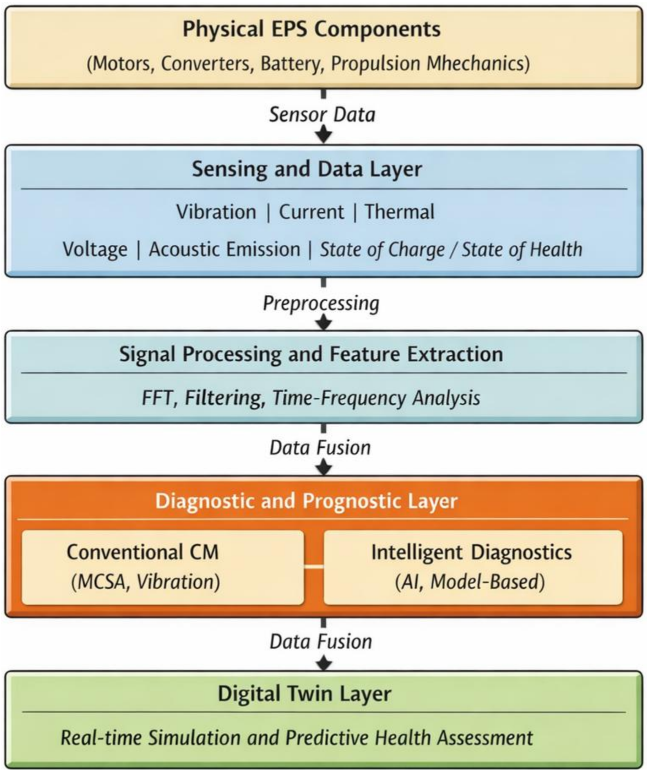

Fig. 2. Integrated CM/FD framework for marine electric propulsion systems

Table 2. Common faults and recommended monitoring methods

Subsystem	Common Faults	Primary CM Methods	Secondary CM Methods
Electric Motor	Bearing wear, Winding short	Vibration Analysis, MCSA	Thermal Monitoring, AE
	Rotor bar break, Eccentricity	MCSA	Vibration Analysis
Power Converter	IGBT failure, Capacitor degrade	Power Electronics CM, Thermal Monitoring	Voltage/Current Waveform Analysis
	Gate driver fault	Gate driver monitoring	-
Battery System	Cell imbalance, Thermal runaway	Voltage/Temp. Monitoring, ISC*	Performance Trending
	Capacity fade	Performance Trending, EIS**	-
Propulsion Mechanics	Shaft misalignment, Cavitation	Vibration Analysis	Acoustic Emission, Thermal
	Thrust bearing wear	Vibration Analysis, AE	Thermal Monitoring

*ISC: Internal Short Circuit Detection,
**EIS: Electrochemical Impedance Spectroscopy

Table 3. CM and FD methods of EPS in marine industry

Method	Parameters Measured	Best for Detecting	Pros	Cons
Vibration Analysis	Acceleration, velocity, displacement spectra	Bearing wear, misalignment, mechanical looseness	Early mechanical fault detection, well-established	Affected by background noise, requires baseline data
Thermal Monitoring	Surface and component temperatures	Overheating, cooling failures, electrical faults	Non-contact, detects thermal anomalies early	Environmental factors affect readings
MCSA	Current waveforms, harmonics	Rotor/stator faults, eccentricity, winding issues	Non-invasive, detects electrical faults early	Load variations affect accuracy
Insulation/PD Testing	Insulation resistance, PD pulses	Winding/cable insulation degradation	Catches insulation breakdown before failure	Requires high-voltage expertise
Power Electronics CM	Switching patterns, ESR, temps	IGBT/capacitor failures, gate driver issues	Critical for converter reliability	High-speed sampling needed
AI/ML Diagnosis	Multiple sensor data patterns	Complex fault patterns, novel anomalies	Handles big data, improves with time	Needs quality training data
Model-Based FD	Model vs actual system residuals	Sensor faults, parameter drift	Doesn't require failure history	Needs accurate system models
Digital Twin	Simulated vs real performance	Predictive failure modes, virtual testing	Enables what-if scenarios	Significant development effort
Acoustic Emission	High-frequency stress waves	Early bearing/crack defects	Detects faults before vibration methods	Sensitive to noise, expert interpretation

For vibration analysis, data is typically processed using fast Fourier transforms (FFT) to convert time-domain signals into frequency spectra for easier fault identification. In MCSA, algorithms like Park's vector modulus or extended Park's vector Approach can be used to detect faults under variable load conditions. This preprocessing stage cleanses data, extracts relevant features, and prepares it for either human analysis or automated diagnosis by machine learning models, turning vast data streams into actionable insights.

3.1. Vibration analysis for condition monitoring

Vibration analysis is a fundamental method for detecting mechanical faults in marine electric propulsion systems [17, 18]. By installing accelerometers on motors, bearings, and thrusters, operators can capture real-time vibration signatures that indicate developing issues. Spectral analysis helps identify specific fault frequencies linked to imbalances, misalignments, or bearing wear. High-frequency vibration monitoring is particularly effective for early-stage bearing degradation before audible noise appears [19]. Advanced signal processing techniques, such as envelope analysis, enhance fault detection in noisy marine environments. Wireless vibration sensors enable remote monitoring in hard-to-reach locations [20]. Integration with AI allows for automated fault classification and trend analysis. It is non-intrusive and provides continuous insight into mechanical health. However, proper sensor placement and baseline data are crucial for accurate diagnostics. Overall, vibration analysis remains a cornerstone of predictive maintenance in marine propulsion systems.

3.2. Thermal monitoring for fault detection

Thermal monitoring tracks temperature variations to identify potential failures in electric propulsion components. Infrared cameras and embedded thermocouples detect abnormal heat patterns in motor windings, power electronics, and battery systems [21]. Overheating often precedes insulation breakdown or semiconductor failures in IGBT modules. Thermal imaging is especially useful for spotting poor electrical connections or cooling system inefficiencies. Real-time temperature trending helps distinguish between normal operational heating and fault-induced hotspots. In marine environments, thermal monitoring must account for ambient conditions like seawater cooling effects. Combining thermal data with other parameters improves fault diagnosis accuracy. AI-driven thermal models can predict failure risks based on historical patterns.

3.3. Motor current signature analysis (MCSA)

MCSA is a powerful electrical-based technique for diagnosing motor and drive faults in propulsion systems. By analyzing current waveforms, it detects anomalies like broken rotor bars, stator winding faults, and air gap eccentricity [15, 22]. Characteristic frequency sidebands in the current spectrum reveal specific mechanical and electrical defects. This method is non-invasive, requiring only current sensors on power cables. MCSA excels at identifying early-stage faults before vibration or temperature changes become apparent. It's particularly valuable for large propulsion motors where direct inspection is difficult. Advanced signal processing algorithms enhance fault detection sensitivity in variable-speed marine applications. However, load variations and power quality issues can complicate interpretation. When combined with vibration and thermal data, MCSA provides comprehensive motor health assessment. Its cost-effectiveness makes it a preferred choice for marine electric propulsion monitoring.

3.4. Insulation resistance and partial discharge testing

Insulation degradation is a critical concern in marine environments due to moisture and salt contamination. Regular insulation resistance testing (Megger tests) measures dielectric strength to predict winding and cable failures. Partial discharge (PD) monitoring detects micro-arcing within insulation before complete breakdown occurs. High-frequency PD sensors identify deteriorating insulation in motors and high-voltage components [23]. Trending insulation resistance values over time reveals progressive moisture absorption or contamination. PD patterns help localize faults within complex winding structures. These methods are particularly important for high-voltage propulsion systems where insulation failure can be catastrophic. Online PD monitoring systems provide continuous assessment without system shutdown. Interpretation requires expertise to distinguish harmful discharges from normal noise. When integrated with environmental sensors, these techniques offer robust protection against insulation-related failures in harsh marine conditions.

3.5. Power electronics condition monitoring

Power electronic converters require specialized monitoring due to their complex failure modes. Gate driver monitoring checks for proper switching signals and detects driver circuit faults. Capacitor health is assessed through equivalent series resistance (ESR) and capacitance measurements. Thermal cycling analysis tracks semiconductor junction temperature variations that lead to solder fatigue. Voltage and current waveform analysis identify abnormal switching patterns or diode failures. Advanced methods like junction temperature estimation using thermal models predict IGBT lifespan. Online monitoring of DC-link capacitors prevents unexpected converter shutdowns. The high switching frequencies in marine drives necessitate high-speed sampling for accurate diagnostics. Machine learning algorithms are increasingly used to correlate multiple parameters for early fault prediction. This comprehensive approach is essential for maintaining reliable power conversion in electric propulsion.

3.6. Data-driven fault diagnosis with AI

Artificial intelligence revolutionizes fault diagnosis by processing vast amounts of sensor data for pattern recognition [24]. Supervised learning algorithms classify known fault types based on historical failure data. Unsupervised learning detects novel anomalies that deviate from normal operation patterns. Deep neural networks analyze complex time-series data from vibration, current, and temperature sensors. Recurrent neural networks (RNNs) are particularly effective for temporal fault progression analysis. AI systems continuously improve diagnostic accuracy through online learning from new cases. Cloud-based AI platforms enable fleet-wide knowledge sharing and benchmarking. Challenges include the need for high-quality training data and computing resources. When properly implemented, AI-driven diagnosis reduces false alarms and enables truly predictive maintenance. This approach represents the future of intelligent marine propulsion health management. Neural networks and ensemble learning models predict degradation trajectories for motors, converters, and batteries. Recurrent neural networks excel in analyzing temporal data, forecasting when failures may occur under specific operational conditions. Such forecasts support maintenance scheduling and spare parts logistics, reducing unscheduled downtime. AI-driven prognostics integrate seamlessly with digital twins, providing near real-time risk assessment dashboards. Results from pilot projects in ferry and offshore supply vessels demonstrate promising accuracy, often exceeding ninety percent in early fault prediction. This capability reshapes marine maintenance strategies into proactive asset management frameworks.

3.7. Model-based fault diagnosis

Model-based methods compare actual system behavior with mathematical models to detect anomalies. Physical models of motors, drives, and mechanical systems simulate expected performance under various conditions. Residual analysis identifies discrepancies between model predictions and sensor measurements. Parameter estimation techniques track changes in system characteristics indicating degradation. Observer-based methods reconstruct unmeasurable states for comprehensive fault detection. These approaches are particularly effective for sensor fault identification and isolation. Challenges include model accuracy requirements and computational complexity. Hybrid approaches combining physical models with data-driven techniques offer improved robustness. Model-based diagnosis provides deep system understanding but requires significant development effort. When properly implemented, it offers reliable fault detection independent of historical failure data.

3.8. Digital twin technology for predictive maintenance

Digital twins create virtual replicas of propulsion systems that mirror real-time operation. Physics-based models combined with live sensor data enable accurate system simulation [25]. Digital twin predicts component stresses and identifies potential failure modes before they occur. Virtual sensors fill gaps where physical sensors are impractical to install. Scenario testing evaluates system response to various fault conditions offline. Continuous synchronization between physical and digital systems ensures model accuracy. Fleet operators use twins for comparative analysis across multiple vessels. It supports decision-making for maintenance planning and operational optimization. Implementation challenges include model complexity and computational requirements. Digital twins act as dynamic replicas of propulsion systems, continuously synchronized with sensor data. Engineers can test operational scenarios virtually, identifying weaknesses without interrupting vessel service. Predictive models embedded within twins simulate thermal stresses, vibration signatures, and electrical loads, forecasting degradation trends. Integration with fleet-wide digital twins provides comparative insights across vessels, highlighting system-specific anomalies. Challenges involve ensuring computational efficiency and maintaining data synchronization accuracy. Emerging cloud-edge architectures address scalability limitations. As adoption expands, digital twins evolve into strategic tools for lifecycle management, enabling optimization of design, operation, and retirement phases of marine assets. Adopting predictive maintenance strategies yields substantial economic benefits. Traditional scheduled maintenance often results in unnecessary part replacements and extended downtime. Predictive analytics minimizes maintenance interventions by forecasting component degradation accurately. Reduced downtime translates into increased vessel availability, directly impacting profitability.

3.9. Acoustic emission monitoring

Acoustic emission (AE) sensors detect high-frequency stress waves generated by developing faults [26, 27]. This method is particularly sensitive to early-stage bearing defects and crack propagation. AE can identify lubrication failures in bearings before vibration analysis detects them. The technique works well in low-speed applications common in marine propulsion. Wireless AE sensors enable monitoring in rotating machinery without slip rings. Advanced signal processing separates relevant emissions from background noise. Pattern recognition algorithms classify emission signatures for specific fault types. AE provides complementary information to vibration analysis for comprehensive bearing health assessment. Challenges include sensor placement optimization and signal interpretation expertise. When properly applied, AE monitoring offers unparalleled early warning for mechanical failures.

Table 4 summarizes reported performance metrics from representative literature, including diagnostic accuracy, detection lead time, and application context for techniques such as MCSA, vibration analysis, and AI-based methods in marine and ship-related propulsion systems.

3.10. Best practices and practical guidelines for CM/FD selection in marine EPS

Table 5 synthesizes insights from Tables 2 and 3 into actionable guidelines, linking subsystem type, operating conditions, recommended monitoring techniques, and implementation considerations.

4. Conclusions and future trends

Condition monitoring and fault diagnosis are essential for ensuring both reliability and efficiency of marine electric propulsion systems. Each monitoring method from vibration analysis to AI-driven diagnostics offers unique advantages for detecting specific failure modes. While vibration and thermal monitoring excel at catching mechanical faults, electrical techniques like MCSA and insulation testing address critical electrical issues. Advanced approaches such as digital twins and AI enable predictive maintenance, reducing unplanned downtime. However, harsh marine environments pose challenges that require robust, integrated monitoring solutions. Combining multiple techniques provides comprehensive system coverage, improving fault detection accuracy. As marine electrification grows, smart monitoring systems will become increasingly vital for operational safety and cost efficiency. Ultimately, a well-designed condition monitoring strategy enhances performance, extends asset life, and supports sustainability goals. Investing in these technologies today ensures more reliable and efficient vessels for future.

Future monitoring landscapes will merge AI, digital twins, and advanced sensing technologies into unified platforms. Optical fiber sensors embedded within structural components will enable distributed strain, temperature, and vibration measurement. Quantum sensors, currently under research, promise unprecedented precision in detecting electrical anomalies. Blockchain technology may secure data exchange across fleets, ensuring trustworthy records for compliance and predictive analytics. Miniaturization of sensors and adoption of wireless communication reduce installation costs while increasing accessibility. Interoperability standards will enable seamless integration across vessels, equipment suppliers, and regulatory bodies. Marine propulsion industry stands at threshold of a paradigm shift where intelligent monitoring ensures sustainability, safety, and profitability.

Table 4. Quantitative performance comparison of CM/FD techniques

Technique	Application Example (Literature)	Reported Performance Metrics	Key Observations
Vibration Analysis	Bearing fault detection in marine motors	Detection lead time: weeks before failure	Highly reliable for mechanical faults; requires baseline data
MCSA	Rotor bar fault detection in ship propulsion motors	Fault detection accuracy: ~80–90%	Non-invasive; sensitive to load variations
Thermal Monitoring	IGBT and winding overheating in marine drives	Hotspot detection prior to insulation failure	Effective for power electronics and batteries
AI-based FD (ML/DL)	Ferry and offshore supply vessel case studies	Diagnostic accuracy >90%; early fault prediction	Superior performance in noisy, variable conditions
Digital Twin-based CM	Integrated EPS health monitoring	Predictive capability under multiple scenarios	Enables "what-if" analysis and maintenance optimization

Table 5. Best practices for CM/FD in marine electric propulsion systems

Subsystem	Operating Conditions	Recommended CM/FD Techniques	Practical Guidelines
Electric Motors	Continuous operation, variable load, humid and salty environment	Vibration Analysis + MCSA + AI-based FD	Combine vibration and MCSA for early fault detection; use AI to compensate for load variations and noise
Power Electronics (Converters, Inverters)	High switching frequency, thermal cycling	Thermal Monitoring + Power Electronics CM + Model-based FD	Prioritize junction temperature estimation; use model-based residuals for early degradation
Battery / Energy Storage Systems	Charge–discharge cycling, thermal stress	Voltage and Temperature Monitoring + AI prognostics	Use AI for state-of-health prediction; integrate thermal monitoring to prevent thermal runaway
Propulsion Mechanics (Shafts, Bearings, Thrusters)	Low-speed, high-torque, harsh vibration	Vibration Analysis + Acoustic Emission	Apply AE for early crack/bearing defect detection; validate findings with vibration trends
Integrated EPS (System-level)	Complex interaction of subsystems	Hybrid CM (Data-driven + Model-based) + Digital Twin	Fuse multi-sensor data in a digital twin environment for predictive maintenance and decision support

References

[1] J.M. Apsley, A. Gonzalez-Villasenor, M. Barnes, A.C. Smith, S. Williamson, J.D. Schuddebeurs, P.J. Norman, C.D. Booth, G.M. Burt, J. McDonald, Propulsion drive models for full electric marine propulsion systems, IEEE Transactions on Industry Applications, 45 (2009) 676-684.

[2] H. Jabari, A. Shafiei Ghazani, F. Jabari, S. Salarkheili, A Review on Propulsion Drive Trains of Electric Ships: Structures, Challenges and Opportunities, Journal of Energy Management and Technology, 9 (2025) 1-13.

[3] X. Xu, X. Yan, K. Yang, J. Zhao, C. Sheng, C. Yuan, Review of condition monitoring and fault diagnosis for marine power systems, Transportation Safety and Environment, 3 (2021) 85-102.

[4] O. AlShorman, M. Irfan, N. Saad, D. Zhen, N. Haider, A. Glowacz, A. AlShorman, A review of artificial intelligence methods for condition monitoring and fault diagnosis of rolling element bearings for induction motor, Shock and vibration, 2020 (2020) 8843759.

[5] M. Cheliotis, I. Lazakis, G. Theotokatos, Machine learning and data-driven fault detection for ship systems operations, Ocean Engineering, 216 (2020) 107968.

[6] N.Z. Zulkifli, B. Ramadevi, K. Bingi, R. Ibrahim, M. Omar, Predicting Remaining Useful Life of Induction Motor Bearings from Motor Current Signatures Using Machine Learning, Machines, 13 (2025) 400.

[7] A. Golovan, V. Mateichyk, I. Gritsuk, A. Lavrov, M. Smieszek, I. Honcharuk, O. Volska, Enhancing Information Exchange in Ship Maintenance through Digital Twins and IoT: A Comprehensive Framework, Computers, 13 (2024) 261.

[8] K. Anitha, R. Vijayakumar, J.G. Jeslin, K. Elangovan, M. Jagadeeswaran, C. Srinivasan, Marine Propulsion Health Monitoring: Integrating Neural Networks and IoT Sensor Fusion in Predictive Maintenance, in: 2024 2nd International Conference on Device Intelligence, Computing and Communication Technologies (DICCT), 2024, pp. 1-6.

[9] A. Hasan, T. Asfihani, O. Osen, R.T. Bye, Leveraging digital twins for fault diagnosis in autonomous ships, Ocean Engineering, 292 (2024) 116546.

[10] M.R. Kabir, D. Halder, S. Ray, Digital twins for iot-driven energy systems: A survey, IEEE Access, (2024).

[11] M. Yazdi, Integration of IoT and edge computing in industrial systems, in: Advances in Computational Mathematics for Industrial System Reliability and Maintainability, Springer, 2024, pp. 121-137.

[12] C.A. Reusser, H.A. Young, J.R.P. Osses, M.A. Perez, O.J. Simmonds, Power electronics and drives: Applications to modern ship propulsion systems, IEEE Industrial Electronics Magazine, 14 (2020) 106-122.

[13] W.P. Symington, A. Belle, H.D. Nguyen, J.R. Binns, Emerging technologies in marine electric propulsion, Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment, 230 (2016) 187-198.

[14] N. Arish, M.J. Kamper, R.J. Wang, Advancements in electrical marine propulsion technologies: A comprehensive overview, SAIEE Africa Research Journal, 116 (2025) 14-29.

[15] D. Li, R. Deng, Z. Zou, B. Huang, F. Gu, A review of fault diagnosis methods for marine electric propulsion system, Proceedings of IncoME-VI and TEPEN 2021: Performance Engineering and Maintenance Engineering, (2022) 971-984.

[16] M. Orhan, M. Celik, A literature review and future research agenda on fault detection and diagnosis studies in marine machinery systems, Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment, 238 (2024) 3-21.

[17] M. Tiboni, C. Remino, R. Bussola, C. Amici, A review on vibration-based condition monitoring of rotating machinery, Applied Sciences, 12 (2022) 972.

[18] M. Romanssini, P.C.C. de Aguirre, L. Compassi-Severo, A.G. Girardi, A review on vibration monitoring techniques for predictive maintenance of rotating machinery, Eng, 4 (2023) 1797-1817.

[19] M.H. Mohd Ghazali, W. Rahiman, Vibration analysis for machine monitoring and diagnosis: A systematic review, Shock and vibration, 2021 (2021) 9469318.

[20] I. Panić, J. Ćelić, A. Cuculić, Wireless condition monitoring of machinery and equipment in maritime industry: an overview, Pomorstvo, 32 (2018) 201-210.

[21] H.N. AL-Jubori, A.-D. Izzat, H. Jerbi, Defect Detection Using Thermography Camera Techniques: A review, Al-Khwarizmi Engineering Journal, 20 (2024) 70-88.

[22] A. Sergakis, M. Salinas, N. Gkiolekas, K.N. Gyftakis, A Review of Condition Monitoring of Permanent Magnet Synchronous Machines: Techniques, Challenges and Future Directions, Energies, 18 (2025) 1177.

[23] Z.H. Bohari, M. Isa, A.Z. Abdullah, A. Ab Rahman, A brief review of partial discharge (PD) detection, recognition and location techniques for liquid and gas insulated high voltage equipment, Journal of Advanced Research in Fluid Mechanics and Thermal Sciences, 64 (2019) 63-76.

[24] T. Song, C. Pang, B. Hou, G. Xu, J. Xue, H. Sun, F. Meng, A review of artificial intelligence in marine science, Frontiers in Earth Science, 11 (2023) 1090185.

[25] D. Zhong, Z. Xia, Y. Zhu, J. Duan, Overview of predictive maintenance based on digital twin technology, Heliyon, 9 (2023).

[26] J.A. Steel, R.L. Reuben, Recent developments in monitoring of engines using acoustic emission, The Journal of Strain Analysis for Engineering Design, 40 (2005) 45-57.

[27] G. Jombo, Y. Zhang, Acoustic-based machine condition monitoring—methods and challenges, Eng, 4 (2023) 47-79.