Prognostics and Health Management for Ships Machinery: A Review of Edge-Intelligence for Asset Integrity

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Abstract

Ship machinery running continuously and selling worldwide, it is crucial to maintain all machinery to protect ships, crew, environment and laws. The current preventive maintenance strategies not able to fulfilled requirement of sensible marine equipment maintenance and huge impact in unexpected breakdowns, operational delays, and significant financial losses. In the era of artificial intelligent (AI) enable Predictive Maintenance (PdM) by using ship machinery data analytics and emerged as a promising solution for forecasting equipment faults and enhancing maintenance operations. Edge computing (EC) model help to reducing computational time, communication delay, improving data secrecy, and minimizing dependence on centralized cloud-based (CB) computing. In this paper present various proposed PdM methods for specific maritime machinery, the existing literature lacks an extensive review of PdM approaches across different marine equipment. To address the gap of literature review, this paper provides an overview of state-of-the-art data-driven PdM techniques in the maritime industry, with particular emphasis on EC architectures. Furthermore, current research challenges, implementation barriers, and future research directions are discussed to advance the implementation of this technology in the field.

Keyword: Predictive Maintenance, artificial intelligence, ship, machinery, edge computing

1. Introduction

The figure 1 shows the maritime industry is poised for a paradigm shift of a magnitude that rivals the historical move from sail to stream propulsion. It transports 80% of trade goods worldwide and every year increase by 2.4% by 2029[1].

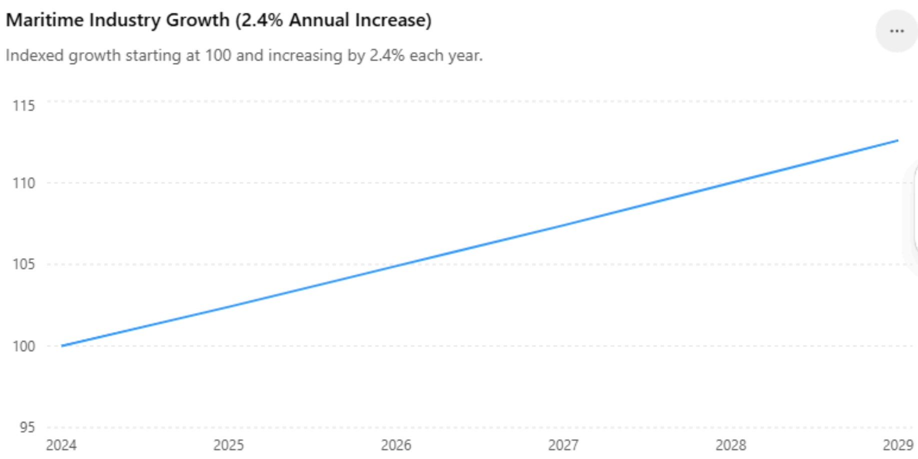

Figure 1: Maritime Industry Growth

This large growth and complex operation require marine equipment all-time availability and safety of the vessel, which is extremely correlated with maintenance operations[2]. The outdated maintenance approach is not effective for marine complex equipment, causing many accidents and often resulting in significant financial losses.[3] Conventional maintenance must advance to a condition-based maintenance approach, also known as PdM. PdM uses a Machine Learning (ML) model to proactively estimate potential machinery failures based on equipment-related operational data-driven understandings[4]. The development of AI and the Internet of Things (IoT) 4.0 has advanced the traditional ship to smart ship[5]. This will enable the remote monitoring of ship parameters, automation of fleet management, reduction of downtime events, and compliance with environmental regulations. However, with advancements in technology, there are real-world challenges in deploying large-scale systems in real maritime environments, communication efficiency, data security, and privacy, especially in the usual cloud-based learning (CBL) approach[6]. In CBL, a huge amount of data must be uploaded to the centre server, which may be subjected to cyberattacks and operational risks. In addition, CBL need to configured with different fleet sizes and vessel types and mitigate this issue, EC paradigms have recently been introduced, confirming secure data privacy and enabling ships to act as edge nodes, thereby reducing latency over the constraints of traditional CB analytics[7]. The embedded system with AI model used at the edge for EC, that can immediately process various sensos of machine and enable proactive fault detection and maintenance reliability on time. Recent paper have observed aspects of fault prediction in the maritime industry. Ma et al. developed CNN-TCN-ATTENTATION for fault detection in marine diesel engines, focused on the UMAP and time-series prediction model for the prediction of the six-cylinder temperature of a diesel engine[8], while Budimar et al. focused on a mathematical model for the analysis of the main engine, while these research offer important evidence on the different aspects of predictive maintenance, they lack a compressive analysis of PdM approaches by the different vessel system[9].As far as we know, no existing study offers a inclusive overview of PdM approaches extending all major vessel types. Considering the substantial potential of deployment PdM strategies into maritime digital twins and the literature gap, this paper aims to provide an summary of the latest data-driven PdM techniques applied across various target vessel systems.

Figure 2 illustrates the structure of this study. Section 2 shows the marine asset monitoring, while section 3 discusses edge intelligent architecture in PdM approaches, Section 4 discusses current research challenges and future directions. Finally, Section 5 concludes the study.

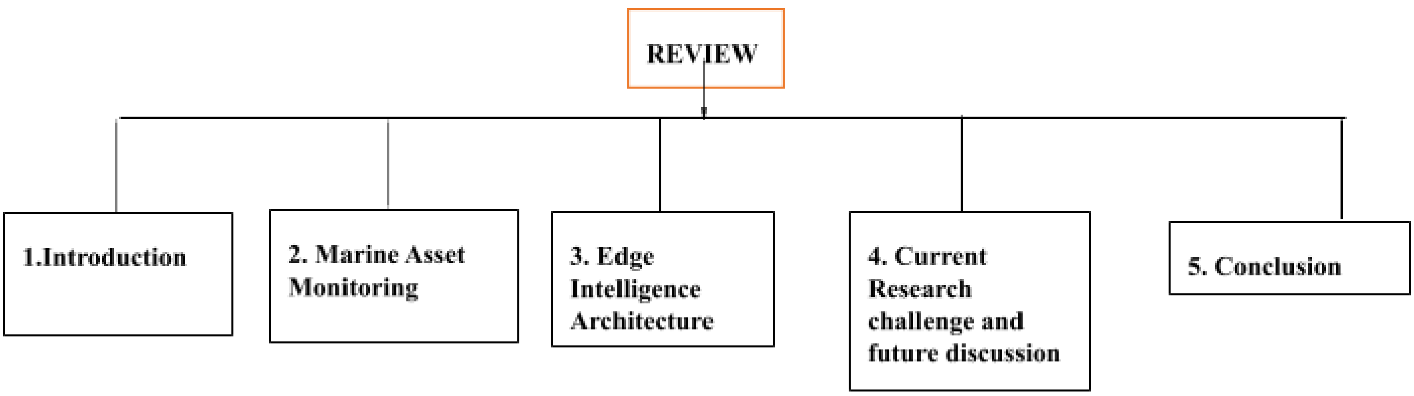

Figure 2. Review structure

2. Marine Asset Monitoring

The figure 3 show the general diagram monitoring system requires the deployment of distributed vibrational, thermal, and tribological sensor nodes capable of localized data preprocessing to minimize bandwidth[10]. At the node EC hardware deployed for measure various sensors feature data, enabling the immediate detection of anomalies prior to transmission to the shipboard digital twin. The application of EC for fault detection reduces the necessity for continuous cloud connectivity by evaluating the severity of faults right at their source [11]. EC can be used domain specific rule with data driven models used for machine failure mechanism [12].

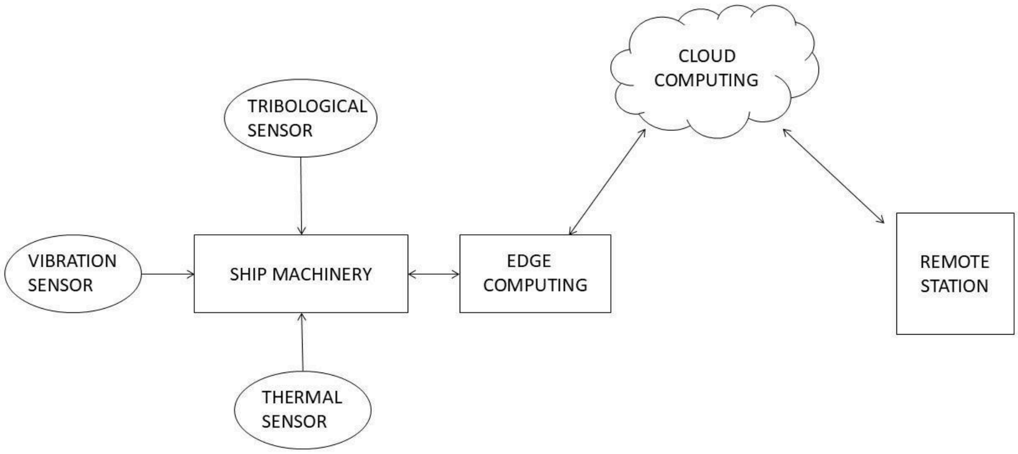

Figure 3: Basic block diagram of deployment of EC technology

Recent developments in vibration-based diagnostics have integrated dense sensor with physics-informed DT to effectively identify structural anomalies amidst complex mechanical noise. Considering the BSA former model is employed to capture spectral dependencies in both directions, which aids in unique bearing wear patterns from transient shaft-periodic orbits.[13]. Synchronized model enhances the extraction of time based and spectral energy features, which are then input into long short-term memory networks for more accurate remaining useful life forecasting than standard regression models provide[14]. PdM with non-cyclic operational telemetry offers a more detailed view of machinery ruin patterns often missed by conventional fault detection process. By integrating various sensors and deep learning models overcome the poor adaptability of purely data-driven approaches, anchoring statistical predictions in established mechanical degradation processes[3]. Domain specific operation wavelet, Fourier transforms, and square envelope enable the systematic extraction harmonic generated data, ensuring neural architectures maintain physical interpret-ability regarding fault-induced cyclo-stationary[15]. Machine get heat up due to friction of running internal parts; to measure and monitor the temperature play pivotal role of machinery health. The integrating these temperature sensors into neural network loss functions, to enable to find fault of strictness and wear evaluations is improved [16]. Machine temperature sensors data and ML open the gateway to identify specific pattern of machine work and find the degradation states using small infrared sensors, maintaining precision even with harmonic state speeds. Multi dimension attention model effectively identifies subtle thermal changes, which are crucial early indicators of diesel engine problems that standard single-scale methods [17]. Showing the complexities of multi dimensions data, modern frameworks employ Temporal Convolution Networks for extracting local features, followed by Cross-former architectures to enhance multi-scale diagnostic accuracy. Additionally, generating exhaust gas temperature time-series through deep hybrid networks allows for the extraction of unique feature sets, outperforming traditional systems in evaluating the health of low-speed two-stroke main engines [18].

Ships need send every 3,6 and 12 monthly lube oil sample data to authorized lab for various test to find the health condition of ship [19]. Ultrasonic and capacitive sensor need to install on machinery for on real time monitoring metal debris, providing crucial information to PdM that link particle density to particular modes of sliding contact surface degradation [20]. However, sensors data and Temporal Convolutional Networks to identify long-term lubricant health condition, providing a more robust degradation valuation than static evaluation methods[21]. However, integrating ferro graph sensors with magnetic pole and advanced models allows for precise wear particle separation, when combined with Mask R-CNN architectures, this improves the classification of irregularities even in highly degraded oil[22].

3. Edge Intelligence Architecture

The development of embedded system with ML algorithm for edge of machinery that merges real-time data fusion with the rigorous power and latency limitations characteristic of shipboard embedded environments[12]. The time delay constraints inference while managing multimodal data streams has been proven through implementation on hardware-accelerated platforms, such as Raspberry Pi-based systems[23]. However, the concept of Federated transfer learning improves EC by allowing marine assets to update models in a decentralized manner, which reduces domain differences in various operational environments while ensuring data privacy [24].

The maritime industry required a robust hardware for complex marine environment for EC. Embedded system; hardware developed with energy-efficient microcontrollers for initial sensor data acquisition with high-performance accelerators accomplished of handling concurrent multi-modal fusion. Feature extraction from sensor vibrational and tribological raw data within the constrained energy parameters of maritime deployments, field-programmable gate arrays are frequently utilized[25]. However, executing sensor data compression methodologies specifically weight pruning and low-rank breakdown is critical for decreasing memory footprints for further transmitting and processing, accelerating deep learning inference on resource-limited embedded hardware[26]. Ships propulsion needs various machinery and generated large volume of different formt of data. EC need data fusion for processing and need to develop robust data fusion model for synchronization of diverse modalities to create a comprehensive, sensors data representation of machine health. ML model extract various features from data, these model harness complementary signal traits to mitigate individual sensor noise, which improves the accuracy of remaining useful life predictions within demanding marine environments[27]. Also, integrating techniques such as robust Mahala Nobis distance mapping and convolutional neural networks facilitates the precise classification of various fault modes, even under the stochastic load conditions encountered during offshore transit[28].

4. Current Research Challenges

AI enabled embedded system open lot of opportunity for PdM for ship machinery, current research is not able to full filled the gap between normal data-driven methodologies and the practical employment of shipboard deployment, particularly regarding the need for robust model for complex marine environment for PdM operations. Furthermore, the transition toward higher degrees of PdM system a shift from purely schedule based, this PdM system help on board crew intensive maintenance cycles toward structured, hierarchical frameworks that ensure system trustworthiness irrespective of human oversight[36]. Additionally, existing maintenance technique frequently overlook the necessity of measuring ambiguity within the inference process, which is essential for the reliable propagation of errors in noisy environment. Furthermore, reliance on high latency CB processing hinders the deployment of truly EC, as real-time anomaly detection requires localized computational frameworks capable of executing complex diagnostic ML algorithms onboard. Although, there is a lack of marine machinery datasets and rule-based training of ML algorithms this enhance EC for the early prognosis maintenance of ship machinery. Onboard EC having such limited storage, power and processing capacity hinder the implementation of computationally demanding ML architectures, prompting the need for the creation of lightweight and energy-efficient ML models [37]. Additionally, AI enabled embedded system are underperform in the intricate marine environment when it comes to predictive maintenance of ship machinery. To tackle these issues, to develop a robust light weight ML model with rule-based algorithms is essential for the PdM of ship machinery.

Conclusion

This review shows the individual sensors and EC architecture for monitoring the machine health index, emphasizing the shift from schedule-based maintenance to an AI-based PdM approach. The major contributions of this study comprise a literature analysis of PdM approaches applied to essential parameters of marine machinery, such as vibration, thermal, and tribological parameters. Compressively, based on the analysis of this study, no single-parameter approach can help as a universal solution, with each system having various sensors and needing to consider all sensor parameters. Taking into consideration Each model presented in this paper has unique advantages and limitations. This paper also presents the most common challenges faced when placing intelligent EC devices. Finally, this paper presents forthcoming research directions. These areas contain the collection of real-time ship machinery data in volume form, advance of lightweight algorithms for training for EC and hyperparameter optimization, and suggesting an advance and secure PdM model for EC devices.

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