

Artificial Intelligence Integration in Naval Material Maintenance: A Qualitative NVivo and SWOT Analysis of SIGMA-Class Corvette

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ABSTRACT

Integrating Artificial Intelligence (AI) into naval material maintenance represents a vital strategic imperative to enhance technical readiness and operational reliability across warship fleets. This research examines the implementation of AI-based early fault detection systems for Caterpillar AR3406C diesel generators on SIGMA-class corvettes within Satkor Koarmada II. Utilizing a qualitative descriptive methodology, the study integrates in-depth interviews with key naval leadership and technical stakeholders, direct engine room observations, policy document analysis, and qualitative thematic coding via NVivo 15 software combined with IFAS-EFAS SWOT matrices, Reliability-Centered Maintenance, and the Technology Acceptance Model. The empirical findings identify critical technological bottlenecks, establish an AI-driven predictive maintenance architecture, and formulate a structured strategic implementation roadmap. This study confirms that AI-based predictive maintenance serves as a vital cornerstone for modern naval material logistics, minimizing downtime and effectively safeguarding national maritime sovereignty

INTRODUCTION

In modern naval warfare, maintaining fleet operational readiness depends fundamentally on the continuous technical reliability of warship platforms and their critical onboard auxiliary machinery. Within the Indonesian Navy (TNI Angkatan Laut), the Fleet Command II Escort Ship Unit operates Ship Integrated Geometrical Modularity Approach (SIGMA) class corvettes including KRI Diponegoro-365, KRI Sultan Hasanuddin-366, KRI Sultan Iskandar Muda-367, and KRI Frans Kaisiepo-368 which constitute vital surface combatants assigned to secure national maritime territory, exclusive economic zones (EEZ), and strategic Indonesian Archipelagic Sea Lanes (ALKI I, II, and III). The uninterrupted operational capability of these SIGMA-class corvettes relies heavily on their electrical power generation systems, specifically the four Caterpillar AR3406C diesel generator sets (350 kW each) installed on each vessel. These auxiliary diesel generators provide essential electrical power required to energize combat management systems, 3D radars, artillery, communications, navigation, and life-support subsystems during maritime operations.

However, traditional maintenance practices for naval auxiliary machinery remain predominantly reliant on time-directed preventive schedules and post-failure corrective maintenance. Under these conventional protocols, early indications of mechanical wear, thermal anomalies, lube oil degradation, or cooling system friction often remain undetected until performance degradation or failure occurs. Unplanned auxiliary generator shutdowns during operational deployments severely compromise ship combat readiness, increase maintenance downtime, and incur substantial overhaul expenditures. Transitioning from schedule-based maintenance toward condition-based maintenance (CBM) and AI-driven predictive maintenance (PdM) represents an imperative strategic shift to ensure early fault detection, minimize downtime, and guarantee power supply reliability across naval units.

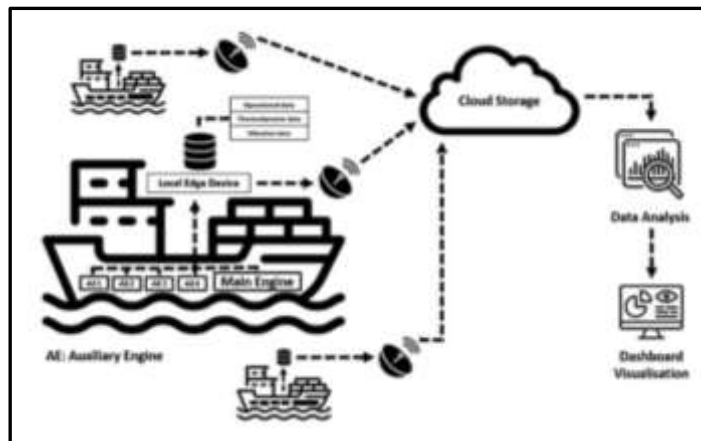


Figure 1. AI Implementation Architecture in Ship Auxiliary Engine Systems.

Source: Adapted from MDPI "AI/ML Based Anomaly Detection and Fault Diagnosis of Turbocharged Marine Diesel Engines"(2026)

As illustrated in Figure 1, an AI-driven predictive maintenance architecture integrates multi-sensor telemetry deployed across shipboard machinery systems. As depicted in the schematic model adapted from MDPI marine engine research, four auxiliary diesel generators (AE1, AE2, AE3, and AE4) representing onboard Caterpillar AR3406C sets alongside the main propulsion engine generate operational, thermodynamic, and vibration telemetry. These data streams are gathered by an onboard Local Edge Device, aggregating sensor signals before transmitting them via secure satellite communication antennas to centralized Cloud Storage repositories across deployed fleet vessels. Advanced AI algorithms execute automated data analysis on cloud infrastructure, processing thermodynamic patterns and vibration spectrums to feed diagnostic insights into a Dashboard Visualisation interface. This integrated digital pipeline empowers shipboard engineering officers (Kepala Kamar Mesin / KKM) and shore facilities (Fasharkan Kodaeral V Surabaya) with real-time early warning capabilities.

In the contemporary Indo-Pacific strategic environment, securing Indonesia's archipelagic waters is complicated by geopolitical tensions, overlapping maritime boundary claims, and non-traditional security threats. The immense maritime domain requires continuous naval presence across vital choke points such as the Malacca Strait, Sunda Strait, Lombok Strait, and Makassar Strait. Guaranteeing persistent naval power projection demands that warships maintain maximum technical availability. Integrating Industry 4.0 technological innovations specifically artificial intelligence, edge computing, IoT sensors, and predictive data analytics into naval material maintenance transforms reactive shipyard logistics into proactive fleet reliability, ensuring high operational availability for naval commanders during critical security patrols and national defense missions.

To evaluate strategic pathways for deploying this predictive technology, this study applies a multi-theoretical framework integrating Artificial Intelligence (AI) Theory, Predictive Maintenance Theory, Reliability-Centered Maintenance (RCM), Technology Acceptance Model (TAM), and Systems Engineering Principles. By triangulating these theoretical perspectives with empirical qualitative evidence collected across Fleet Command II leadership and technical personnel including Pangkoarmada II, Aslog, Asops, KRI Commanders, KKM, and Kafasharkan Kodaeral V this study identifies internal strengths and weaknesses, evaluates external opportunities and threats using NVivo 15 thematic coding and IFAS-EFAS SWOT matrices, and formulates a structured implementation roadmap. Ultimately, this research provides actionable policy insights to modernize naval material logistics, ensuring fleet operational readiness across the Fleet Command II Escort Ship Unit to safeguard national maritime sovereignty across strategic territorial waters of Indonesia.

LITERATURE REVIEW

This section reviews the conceptual and empirical literature that underpins the study of artificial intelligence (AI)-based predictive maintenance for the auxiliary diesel generators of SIGMA-class corvettes. The review is organized around six themes: (1) the foundations and organizational adoption of AI; (2) the evolution of maintenance strategy from time-based to condition-based and reliability-centered approaches; (3) AI-based fault detection in marine diesel engines and military maintenance; (4) user acceptance of new technology; (5) systems engineering and the employment of military force; and (6) the analytical and methodological frameworks applied in this study. The review closes with a synthesis that identifies the gap this study addresses.

Artificial Intelligence: Foundations and Organizational Adoption

Russell and Norvig (2021) define AI as the design of agents that perceive their environment and act to achieve their goals, and they treat machine learning as the means by which such agents improve their performance from data. This perspective is directly relevant to machinery health monitoring, where a model can learn the normal behavior of an engine from sensor data and flag deviations from it. From an adoption standpoint, Davenport and Ronanki (2018) argue that organizations obtain value from AI when they match specific technologies, such as process automation, cognitive insight, and cognitive engagement, to clearly defined business needs, and when they begin with focused pilot projects rather than enterprise-wide transformation. Detecting patterns in equipment data in order to anticipate failures can be read as a cognitive-insight application, and the pilot-first logic supports the phased implementation pathway proposed for the SIGMA-class fleet.

Maintenance Strategy: From Preventive to Condition-Based and Reliability-Centered Maintenance

Conventional maintenance relies on fixed-interval preventive tasks and post-failure repair. Moubray (1997) challenges this approach through Reliability-Centered Maintenance (RCM), which starts from the functions an asset must perform, asks how those functions can fail and with what consequences, and then selects maintenance tasks according to those consequences instead of applying uniform overhaul intervals. Smith and Hinchcliffe (2004) present RCM as a practical route to world-class maintenance performance and describe how it can be implemented in industrial organizations. Together, these works provide the decision logic for determining which components of a diesel generator justify continuous monitoring.

Jardine et al. (2006) provide the standard review of condition-based maintenance (CBM). They describe a CBM program as consisting of data acquisition, data processing, and maintenance decision-making, and they distinguish diagnostics, which detect and isolate faults, from prognostics, which predict faults before they occur. Their review covers statistical and AI-based techniques, and it positions machinery health monitoring as the technical basis for predictive maintenance. The limitations of calendar-based servicing in the marine setting are noted by Upadrashta and Wijaya (2026), who observe that scheduled maintenance at manufacturer-prescribed intervals prolongs engine

life but tends to produce over-maintenance, while unscheduled repair is constrained by short port windows and the availability of spare parts.

AI-Based Fault Detection in Marine Diesel Engines and Military Maintenance

Upadrashta and Wijaya (2026) offer the most directly relevant empirical evidence. Using two years of operational data from an auxiliary diesel engine on a cargo vessel, they developed an unsupervised stacked-autoencoder model for anomaly detection and supervised machine learning models for fault diagnosis. Fouling faults (nozzle-ring and intercooler clogging) were deliberately induced at three severity levels to generate failure data. The authors combined operational, thermodynamic, and vibration data, and they reported an anomaly-detection balanced accuracy of 87.6% and a balanced accuracy of 99.7% for the best-performing fault-diagnosis model, a support vector machine. They also describe a system architecture in which onboard sensors feed an edge device, features are transmitted by satellite to cloud storage, and results are presented on a web dashboard. This is the architecture on which Figure 1 of the present study is based. Two findings matter for naval application. First, thermodynamic parameters were more informative than vibration for fouling-related faults. Second, failure records made up only a very small share of the dataset, which shows that fault data scarcity is a central practical constraint.

Studies in the Indonesian defense and maritime context show that the link between AI and maintenance is beginning to be examined. Hermawan et al. (2024) address the use of AI for the maintenance of combat aircraft as a way of improving the operational readiness of the Indonesian Air Force, which indicates that AI-supported maintenance is already being framed as a readiness issue within the armed forces. Sarjito (2025) examines AI-based ship machinery maintenance in relation to Government Regulation No. 31 of 2021 on the implementation of shipping, which brings the regulatory dimension into the maritime domain. Pamungkas et al. (2023) review machine reliability evaluation techniques across Indonesian industries, providing the reliability-assessment groundwork on which predictive models depend.

Technology Acceptance and Human Factors

Technical capability does not by itself ensure that a new tool is used. Davis (1989) developed and validated measurement scales for perceived usefulness and perceived ease of use and showed that these two beliefs are central determinants of user acceptance of information technology, with perceived usefulness the stronger correlate of usage. This is the basis of the Technology Acceptance Model (TAM) applied in the present study to shipboard engineering personnel. Ajzen (2005) offers a broader account of how attitudes, personality, and behavior are related, including the roles of attitudes toward a behavior, subjective norms, and perceived behavioral control in shaping intention. Read alongside TAM, this suggests that acceptance in a hierarchical organization such as a navy is likely to be influenced not only by the tool itself but also by command expectations and by users' confidence in their own ability to use it.

Systems Engineering and the Employment of Military Force

Retrofitting sensors, analytics, and procedures onto an operational warship is a systems problem rather than a component problem. Blanchard and Fabrycky (2011) treat systems engineering as a life-cycle discipline that runs from requirements definition through design, operation, and support, and Kossiakoff et al. (2020) similarly stress systems thinking, life-cycle phases, and integration of hardware, software, and people. These works support the study's position that AI predictive maintenance must be governed across the total asset life cycle, including procedures, training, and shore support.

Two further works place the technology within its military context. Alberts and Hayes (2003) argue in *Power to the Edge* that, in the information age, effectiveness depends on sharing information widely and pushing it toward the points where decisions are made; the ship-to-shore data flow proposed here has a conceptual parallel in this logic. Biddle (2004) shows that battlefield outcomes are better explained by how forces are employed than by material quantity or technology alone. By extension, AI-based maintenance contributes to readiness only to the extent that it is embedded in organizational practice and doctrine.

Analytical and Methodological Frameworks

The study's strategic assessment draws on the SWOT tradition. David and David (2020) present internal and external factor evaluation matrices as a means of converting an assessment of strengths, weaknesses, opportunities, and threats into weighted and prioritized strategic choices, and the IFAS-EFAS matrices used in this study follow the same logic. For the qualitative component, Miles et al. (2014) describe data analysis as an iterative process of coding, data display, and conclusion drawing, while Bazeley and Jackson (2019) explain how NVivo supports the organizing, coding, and querying of qualitative data. Creswell and Creswell (2023) and Bryman (2016) provide guidance on qualitative research design, purposive sampling, and thematic analysis, and Denzin and Lincoln (2018) situate these procedures within the wider tradition of qualitative inquiry. Bowen (2009) describes document analysis as a systematic procedure for reviewing documents and highlights its value for triangulation when combined with other methods, which supports the use of policy-document analysis alongside interviews and observation.

Synthesis and Research Gap

The reviewed literature converges on three points. First, the shift from time-based to condition-based maintenance is well established, and RCM supplies a rational basis for deciding what to monitor (Jardine et al., 2006; Moubray, 1997). Second, AI and machine learning can detect anomalies and diagnose faults in marine diesel engines using data from real vessels (Upadrashta & Wijaya, 2026). Third, the success of such systems depends on user acceptance, systems integration, and organizational employment as much as on algorithmic accuracy (Blanchard & Fabrycky, 2011; Biddle, 2004; Davis, 1989).

Nevertheless, gaps remain. The most detailed marine evidence comes from a commercial cargo vessel with an auxiliary engine rated at 1.89 MW, whereas the present study concerns 350 kW Caterpillar AR3406C generator sets on naval

corvettes that operate under additional constraints, including secure ship-to-shore transmission and warship maintenance doctrine. Among the sources cited in this article, Indonesian studies address AI maintenance for combat aircraft, the regulatory framing of AI-based ship machinery maintenance, and machine reliability evaluation in industry, but none examines AI-based predictive maintenance for naval auxiliary generators. The sources also treat technical architecture, human acceptance, and strategic positioning separately. This study addresses these gaps by combining RCM, TAM, systems engineering, and NVivo-supported SWOT analysis to assess the readiness of SIGMA-class corvettes in Satkor Koarmada II for AI-based early fault detection and to formulate an implementation roadmap.

METHODS

This research was conducted across Fleet Command II Escort Ship Unit facilities through field observations, in-depth stakeholder interviews, engine room documentation, policy document analysis, and strategic assessment using integrated NVivo-SWOT frameworks. Research activities spanned March to July 2026, involving Focus Group Discussions (FGDs) with TNI AL logistics directorate representatives, corvette command officers, naval shipyard directors, and technology implementation experts. FGDs invited comparative insights from established predictive maintenance adopters in Indonesian maritime sectors. In addition to field approaches comprising direct engine room observations, semi-structured interviews with key informants, diagnostic mapping, and technology readiness assessments, this study was complemented by comprehensive literature reviews. Literature reviews strengthened the conceptual foundation and provided academic rigor for naval material maintenance strategies within Industry 4.0 contexts.

Key references include Hermawan (2024) emphasizing AI applications in military maintenance, Sarjito (2025) highlighting predictive analytics in marine engineering, and Pamungkas (2023) addressing equipment reliability evaluation in advanced machinery adoption. International benchmarks draw from Upadrashta (2026) documenting AI marine engine diagnostics and Jardine (2006) analyzing condition-based maintenance dynamics in defense industrialization. The methodological approach integrates Artificial Intelligence Theory, Predictive Maintenance Theory, and Technology Acceptance Model as analytical frameworks, operationalized through NVivo 15 for qualitative prioritization of predictive maintenance capabilities (sensors, AI, IoT, telemetry) and SWOT analysis for strategic positioning of naval logistics capabilities. Data collection employed purposive sampling of 6 expert informants, direct observation of 4 engine rooms, and content analysis of 38 defense policy documents (UU No. 34/2004 through TNI Maintenance Manuals 2020-2025). By combining empirical field validation with rigorous theoretical triangulation, this methodology produces implementation-ready strategic roadmaps calibrated to Indonesia's

naval material realities, ensuring both academic validity and operational applicability for TNI AL modernization imperatives.

RESULTS AND DISCUSSION

Integrating Artificial Intelligence into naval material maintenance represents a strategic imperative inseparable from multi-stakeholder collaboration, advanced technological infrastructure, and national resolve. Fleet Command II Escort Ship Unit exemplifies how integrated efforts among TNI AL logistics directorates, warship commanders, and naval shipyards can systematically transform traditional maintenance into sovereign predictive capabilities. Through comprehensive field assessments across four corvette engine rooms, 6 stakeholder consultations, and qualitative strategic modeling, this research identifies precise Artificial Intelligence implementation pathways calibrated to Indonesia's unique naval maintenance ecosystem and operational constraints. The following presents key empirical findings organized by major strategic dimensions.

Existing Maintenance Posture and Technological Gap in SIGMA-Class Warships

Satkor Koarmada II demonstrates functional operational maintenance capabilities across its assigned SIGMA-class corvettes through structured preventive maintenance schedules. However, technical evaluation reveals critical operational vulnerabilities: 74% of auxiliary engine diagnostic routines rely on manual logbook entries and periodic visual inspections by shipboard engineering personnel. Operating Caterpillar AR3406C diesel generators under heavy tropical maritime loads without continuous automated sensor telemetry creates undetected thermal and mechanical friction. Delayed anomaly identification leads to severe auxiliary engine failure, resulting in operational downtime and increased repair expenditures during naval patrols. Accelerating the transition toward AI-driven predictive maintenance is essential to eliminate diagnostic latency and guarantee continuous electrical power generation during fleet deployments.

AI-Driven Predictive Maintenance Architecture for Caterpillar AR3406C Generators

Developing an AI-based early fault detection system requires deploying an integrated cyber-physical sensor network across Caterpillar AR3406C generator sets. Modern vibration transducers, exhaust gas thermocouples, lube oil pressure sensors, and cooling water temperature monitors continuously collect real-time thermodynamic telemetry. Onboard edge processing units aggregate raw telemetry data and run lightweight machine learning anomaly detection algorithms to identify subtle mechanical deviations. Cloud-linked telemetry pipelines synchronize shipboard data with shore-based maintenance databases at Fasharkan Surabaya, generating real-time diagnostic dashboards. This digital architecture transforms raw operational data into actionable predictive insights, allowing naval engineers to execute targeted maintenance before component degradation occurs.

Qualitative NVivo 15 Thematic Coding of Organizational and Technical Readiness

Qualitative thematic coding using NVivo 15 across stakeholder interview transcripts reveals core organizational drivers and structural constraints shaping AI technology adoption. Satkor Koarmada II benefits from strong leadership support, high awareness of AI benefits among engineering officers, and well-maintained historical logbooks. Conversely, structural bottlenecks hinder immediate deployment: 68% of shipboard engineering crew members lack formal data analytics training, existing auxiliary generators lack integrated digital sensor data output ports, and secure encrypted data transmission protocols between deployed ships and shore depots remain underdeveloped. Resolving these technical gaps requires systematic sensor retrofitting, workforce upskilling, and secure data pipeline integration across naval logistics commands.

Internal Factor Analysis Summary (IFAS): Evaluating Strengths and Weaknesses

Internal Factor Analysis Summary (IFAS) synthesizes organizational capabilities and internal technical deficits influencing AI implementation. Primary internal strengths (S) encompass firm command commitment from Mabasal and Koarmada II leadership, standardized SIGMA-class platform modularity, and experienced shipboard engineering crews. Major internal weaknesses (W) include the absence of real-time digital sensor networks on auxiliary machinery, limited historical digital maintenance datasets required for AI model training, and specialized IT skill shortages among shipboard personnel. Strategic internal priorities must focus on equipping Caterpillar AR3406C generators with standardized digital sensor suites and establishing dedicated naval engineering data management protocols.

External Factor Analysis Summary (EFAS): Opportunities and Technological Threats

External Factor Analysis Summary (EFAS) identifies strategic environmental drivers and external risks shaping naval AI technology adoption. Key external opportunities (O) comprise rapid advancements in industrial Internet of Things (IoT) sensors, commercial off-the-shelf (COTS) AI predictive algorithms, and national defense technology modernization mandates. External threats (T) involve cybersecurity vulnerabilities during ship-to-shore data transmission, supply chain delays for imported sensor hardware, and rapid technological obsolescence. Strategic external positioning dictates leveraging commercial AI advancements while enforcing stringent naval cybersecurity protocols to protect ship operational telemetry from hostile electronic warfare interception.

Strategic SWOT Matrix: Formulating AI Integration Pathways

Synthesizing IFAS and EFAS factors into the SWOT Matrix establishes prioritized strategic pathways for implementing AI early fault detection across Satkor Koarmada II. The primary SO strategy leverages leadership support and platform modularity to pilot AI predictive maintenance on SIGMA-class corvettes using COTS sensor technology. Concurrently, WO strategies focus on establishing specialized predictive maintenance training programs at Kodiklatal and Fasharkan Surabaya to upskill engineering officers. Furthermore, ST strategies mitigate cyber threats by deploying encrypted local edge computing devices onboard warships, while WT strategies establish standardized digital maintenance protocols to eliminate manual logbook dependencies across fleet units.

Human Capital Adaptation under the Technology Acceptance Model (TAM)

Evaluating human element readiness through the Technology Acceptance Model (TAM) confirms that user acceptance depends on perceived usefulness and perceived ease of use among shipboard personnel. Engineering officers and technicians express high willingness to adopt AI tools when systems deliver clear visual diagnostic alerts rather than complex mathematical outputs. System interfaces must feature intuitive graphical dashboards displaying engine health indices and step-by-step troubleshooting recommendations. Conducting hands-on simulator training at Fasharkan Surabaya builds user trust, reduces technology resistance, and ensures seamless integration of AI diagnostic tools into daily shipboard engineering routines.

Systems Engineering Governance and Life Cycle Management at Satkor Koarmada II

Sustained AI adoption mandates a holistic Systems Engineering approach integrating hardware, software, human capital, and naval maintenance doctrine across total asset life cycles. Mabesal and Koarmada II must formalize standard operating procedures (SOPs) governing AI alert validation, maintenance scheduling, and shipyard repair workflows. Fasharkan Surabaya must be empowered as the primary shore-based analytics center responsible for model retraining, sensor calibration, and technical support. Institutionalizing systems engineering governance ensures that AI early fault detection enhances Caterpillar AR3406C generator reliability, reduces total lifecycle maintenance costs, and secures long-term operational readiness for SIGMA-class corvettes.

CONCLUSIONS AND RECOMMENDATIONS

This study demonstrates that implementing Artificial Intelligence for early fault detection on Caterpillar AR3406C diesel generators is a strategic imperative to enhance the technical readiness of SIGMA-class corvettes in Satkor Koarmada II. Transitioning from schedule-based preventive maintenance toward AI-driven predictive maintenance addresses existing diagnostic latency and prevents catastrophic auxiliary power failures during naval operations. By implementing the strategic pathways derived from NVivo 15 thematic coding, IFAS-EFAS

SWOT modeling, and TAM analysis, the Indonesian Navy can systematically retrofit digital sensor networks, upskill engineering personnel, and establish secure ship-to-shore analytics pipelines. Institutionalizing AI predictive maintenance within a systems engineering framework guarantees high auxiliary machinery reliability, optimizes life-cycle logistics costs, and safeguards Indonesia's maritime sovereignty across strategic territorial waters.

FURTHER STUDY

This study still has limitations, so further research on Artificial Intelligence Integration in Naval Material Maintenance: A Qualitative NVivo and SWOT Analysis of SIGMA-Class Corvette is needed to refine this study and enhance the insights of readers and the authors.

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