

Applications of Artificial Intelligence in Predictive Maintenance of Naval Engineering Systems

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Abstract

Naval vessels depend on complex engineering systems, including propulsion plants, power generation, auxiliary machinery, and hull and platform equipment, whose failure can compromise safety, readiness, and mission success. Traditional maintenance based on fixed schedules or reaction to breakdowns is costly and often poorly matched to the real condition of equipment. This article examines the applications of artificial intelligence in the predictive maintenance of naval engineering systems. It reviews the evolution of maintenance strategies, the data acquisition and monitoring infrastructure that underpins predictive approaches, and the machine learning methods used for fault detection, diagnosis, and prognosis. It then considers applications to propulsion, power, and auxiliary systems, the role of digital twins and integrated health management, and the implementation challenges of data quality, model trust, and cybersecurity. Drawing on research in prognostics and health management, machine learning, and naval engineering, the analysis finds that artificial intelligence can reduce unplanned downtime, improve the targeting of maintenance effort, and strengthen operational readiness, but that benefits depend on reliable data, validated models, skilled personnel, and integration with logistics. The article concludes with recommendations for naval organisations seeking to adopt predictive maintenance responsibly and effectively.

Keywords: predictive maintenance, artificial intelligence, naval engineering, condition monitoring, prognostics

INTRODUCTION

A warship is a concentration of machinery operating in demanding conditions. Gas turbines and diesel engines drive the propulsion shafts, generators supply electrical power, pumps and compressors circulate fluids, and a wide array of

auxiliary systems supports habitability, damage control, and combat capability. These systems operate in salt laden air, under shock and vibration, and often at remote locations where repair facilities are far away. When they fail, the consequences range from reduced speed and cancelled operations to danger to the ship and crew. Maintenance is therefore a major factor in naval readiness and cost. Navies spend large sums on keeping ships and submarines serviceable, and a significant share of that expenditure is incurred to replace parts that were still serviceable or to repair failures that could have been foreseen. Mobley, in his introduction to predictive maintenance, argued that maintenance is often one of the largest controllable costs in industrial operations and that moving from reactive and schedule driven methods to condition driven methods can yield substantial savings and improved availability (Mobley, 2002). Recent advances in sensing, computing, and artificial intelligence have made predictive maintenance far more capable. LeCun, Bengio, and Hinton described how deep learning allows computational models to discover representations in raw data at multiple levels of abstraction, enabling breakthroughs in tasks such as pattern recognition from complex signals (LeCun et al., 2015). These techniques are now applied to the vibration, temperature, pressure, and acoustic data produced by machinery, with the aim of detecting faults early and forecasting remaining useful life. This article asks how artificial intelligence is being applied to predictive maintenance in naval engineering and what conditions determine success. It proceeds through nine thematic sections addressing maintenance challenges, the evolution of strategies, data infrastructure, machine learning methods, applications to major systems, digital twins and health management, implementation challenges, logistics and economics, and future directions. A summary and a list of references follow.

Maintenance Challenges in Naval Engineering Systems:

Naval engineering systems present several distinctive maintenance challenges. First, reliability requirements are high. Warships must be ready for operations at short notice, and a failed system can have operational and safety consequences far greater than in many commercial settings. Second, the operating environment is severe. Machinery experiences varied loads, sudden manoeuvres, shock from weapons and sea conditions, and exposure to corrosion. Third, ships operate at a distance from support. A vessel deployed for months must be largely self sufficient, with maintenance performed by a limited number of skilled personnel using the spares that are on board. Unexpected failures can force a ship to abandon its mission or return to port. Fourth, naval platforms have long service lives, often thirty years or more, so ageing becomes a major factor and new technologies must be integrated into old systems. Fifth, naval fleets are heterogeneous. Different classes of ship use different engines, controls, and auxiliary systems, and even ships of the same class may be configured differently. This variety complicates the development of standard models and requires careful validation for each application. Sixth, operational security constraints limit the connectivity of ships and the sharing of data with industry, which affects how analytics can be deployed. Traditional strategies struggle with these challenges. Time based maintenance may replace components that are still healthy, wasting resources and introducing the risk of maintenance induced faults. Reactive maintenance accepts failures and their consequences. Condition based approaches improve matters but often rely on simple thresholds that miss complex or gradual degradation. These limitations create the opportunity for more intelligent approaches.

Evolution from Corrective to Predictive Maintenance:

Maintenance strategies can be arranged along a continuum. The earliest and simplest approach is corrective maintenance, in which equipment is run until it fails and is then repaired. It minimises planned effort but exposes operators to unexpected breakdowns. Preventive maintenance introduces scheduled inspections and replacements at fixed intervals of time or usage, which reduces failures but may be wasteful. Condition based maintenance schedules work according to the observed state of equipment. Jardine, Lin, and Banjevic reviewed methods for machinery diagnostics and prognostics and described condition based maintenance as a programme that recommends decisions on the basis of information collected through condition monitoring, comprising data acquisition, data processing, and decision making (Jardine et al., 2006). This framework forms the basis for modern predictive approaches. Predictive maintenance extends condition based maintenance by forecasting future condition and remaining useful life, so that interventions can be scheduled at the most appropriate time. Lee, Bagheri, and Kao described cyber physical architectures in which connected machines, sensors, and analytics produce self awareness of assets and enable predictive decisions at scale (Lee et al., 2015). Artificial intelligence is central to this evolution, because it allows models to learn complex relationships among many variables and to adapt as data accumulate. The figure below presents an illustrative comparison of unplanned downtime across maintenance strategies, expressed as an index in which reactive maintenance is set to one hundred. The values are stylised to show the relative direction discussed in the literature and should not be read as measured data.

Data Acquisition and Condition Monitoring Infrastructure:

Predictive maintenance depends on data. On a naval vessel, data come from a range of sources. Vibration sensors on rotating machinery reveal imbalance, misalignment, bearing wear, and gear problems. Temperature and pressure sensors track thermal and hydraulic conditions. Oil analysis detects wear particles and contamination. Acoustic and

ultrasonic sensors identify leaks and abnormal operation. Electrical measurements monitor motors and generators, while performance data such as fuel flow, speed, and power output indicate efficiency. Ships often already generate large volumes of data through their integrated platform management systems, which record operating parameters and alarms. The challenge is to collect, store, and organise these data in a form suitable for analysis. Edge computing on board can perform initial processing and reduce the need to transmit large volumes ashore, which is important given limited bandwidth. Shore based facilities can then aggregate data from multiple ships to build fleet wide models. Data quality is a critical factor. Sensors may drift, fail, or be poorly calibrated, and records may contain gaps and errors. Labels that identify when and how failures occurred are often scarce, because failures are rare and records may be incomplete. Lei and colleagues, in a systematic review of machinery prognostics, emphasised that the process from data acquisition through health indicator construction to remaining life prediction depends on the quality and representativeness of the underlying data (Lei et al., 2018). Infrastructure also includes the means of integrating data with maintenance management systems, so that predictions translate into work orders, parts requests, and scheduling decisions. Without this link, analytics may produce interesting insights that never reach those who can act. Standards for data formats and interfaces help to avoid fragmentation and to enable the reuse of models across platforms.

Machine Learning Methods for Fault Detection and Prognosis:

Several families of machine learning methods are used in predictive maintenance. Supervised learning uses labelled examples of normal and faulty operation to train classifiers that detect and diagnose faults. Common techniques include support vector machines, random forests, gradient boosting, and neural networks. Carvalho and colleagues, in a systematic review of machine learning applied to predictive maintenance, found that random forests, neural networks, support vector machines, and related methods are widely used, and that choice depends on data characteristics and the goal of the analysis (Carvalho et al., 2019). Unsupervised and semi supervised methods are valuable where fault examples are rare. These methods learn a model of normal behaviour and flag deviations as anomalies. Techniques include clustering, autoencoders, and statistical process monitoring. They can detect novel faults that were not anticipated, although they may also generate false alarms when operating conditions change. Deep learning has expanded the toolkit. Zhao and colleagues reviewed deep learning applications to machine health monitoring and described architectures such as convolutional networks, recurrent networks, and autoencoders that learn features automatically from raw sensor signals, reducing reliance on manual feature engineering (Zhao et al., 2019). Such methods have shown strong performance on tasks such as bearing fault diagnosis and remaining useful life prediction, particularly when large datasets are available. Prognostics, the estimation of remaining useful life, builds on detection and diagnosis. Approaches include data driven regression models, physics based degradation models, and hybrids that combine both. Benchmark datasets, such as those generated from simulated engine degradation, have helped researchers compare methods (Saxena et al., 2008). A practical caution is that algorithms performing well on benchmarks may not transfer directly to real fleets, where data are noisy, operating conditions vary, and failure modes differ. Validation on representative naval data is therefore essential.

Application to Propulsion, Power, and Auxiliary Systems:

Propulsion plants are the most prominent application. Coraddu and colleagues studied machine learning approaches for improving condition based maintenance of naval propulsion plants and showed that data driven models could estimate the decay state of components such as the compressor and turbine of a gas turbine propulsion system from measurements already available on board, supporting maintenance planning without additional intrusive inspection (Coraddu et al., 2016). Their work illustrates how existing sensor data, combined with learning algorithms, can reveal gradual degradation that simple thresholds miss. In diesel and gas turbine engines, typical targets include fouling of compressors, wear of bearings, injector problems, cooling system degradation, and combustion irregularities. Models can combine vibration, temperature, pressure, and performance data to distinguish between faults with similar symptoms. Early detection allows operators to adjust operating profiles, schedule cleaning or repair during planned availability, and avoid catastrophic failure. Electrical power systems form a second area. Generators, switchboards, transformers, and power electronics are critical to ship operation, particularly on vessels with integrated electric propulsion. Machine learning can monitor electrical signatures and thermal patterns to detect insulation degradation, winding faults, or abnormal loading. In ships with large pulsed loads, such as advanced sensors and future directed energy systems, predictive monitoring helps protect stability and avoid overload. Auxiliary systems, including pumps, compressors, heating and cooling plants, hydraulic systems, steering gear, and fire fighting equipment, also benefit. Although individual units may seem minor, their failure can disable important functions. Fleet wide analysis can identify recurring weaknesses and inform design improvements. Hull and structure monitoring, using strain gauges and corrosion sensors, adds a further dimension, giving early warning of fatigue and coating breakdown. In submarines, acoustic signatures of machinery are also relevant, since abnormal noise can indicate both a technical problem and an increased detectability risk.

Digital Twins and Integrated Health Management:

A digital twin is a virtual representation of a physical asset that is continuously updated with data from its real counterpart. Grieves and Vickers described the concept as a means of mitigating unpredictable and undesirable emergent behaviour in complex systems by linking physical products with virtual models throughout their lifecycle (Grieves and Vickers, 2017). Tao and colleagues reviewed digital twin applications in industry and noted their use in design, manufacturing, and prognostics and health management, where they combine physics based models with operating data to simulate and predict behaviour (Tao et al., 2019). For naval engineering systems, a digital twin of a propulsion plant or a generator can be used to estimate internal conditions that cannot be measured directly, test the effect of different operating profiles on component wear, and simulate the consequences of faults. When combined with machine learning, the twin can improve predictions by providing a physical context for data driven models, which is especially useful when failure data are scarce. Integrated health management brings together monitoring, diagnosis, prognosis, and decision support at the platform and fleet levels. At the ship level, a health management system collects data from many subsystems, assesses the condition of each, and presents the crew with prioritised alerts and recommendations. At the fleet level, shore based analysts compare ships, identify common trends, and update models. Results feed into maintenance planning, supply chain decisions, and design feedback. These systems must be designed with the user in mind. Alerts that are too frequent or poorly explained will be ignored, while those that are clear, prioritised, and linked to actions will be trusted. Explanation of the reasons for a prediction, including the key signals and the confidence level, helps engineers to judge and challenge the output. Integration with existing platform management systems and maintenance software is also essential, so that the health management function becomes part of daily workflow rather than a separate tool.

Implementation Challenges of Data Quality, Trust, and Security:

Despite its promise, predictive maintenance faces substantial implementation challenges. The first concerns data. Many ships lack sensors on key components, and existing data may be stored in incompatible systems or not retained at all. Failure events are rare and poorly documented, which hampers training of supervised models. Data collected under one operating regime may not represent others, and sensor faults can mimic equipment faults. Careful data curation, labelling, and governance are required. The second challenge is model validity and trust. Machine learning models can perform well on historical data and yet fail under new conditions, such as a different operating profile or a modified component. Black box models make it difficult for engineers to understand why an alert has been raised. Lei and colleagues stressed that prognostic methods must be evaluated for reliability and robustness before deployment in critical applications (Lei et al., 2018). Verification, validation, and continuous monitoring of model performance are therefore essential, along with transparent reporting of uncertainty. The third challenge is human and organisational. Engineers and maintainers must be trained to interpret analytics, and organisations must adapt procedures so that predictions are acted upon. Resistance may arise from concerns that automation will replace expertise, or from reluctance to defer maintenance on the basis of a model. Building trust requires pilot projects that demonstrate value, involvement of operators in design, and clear accountability for decisions. The fourth challenge is security. Predictive maintenance systems connect operational technology with data networks and shore facilities, which creates cyber exposure. Svilicic and colleagues showed that shipboard systems can contain vulnerabilities arising from weak authentication and inadequate segregation (Svilicic et al., 2019). An attacker able to manipulate sensor data or models could cause false alarms, hide real faults, or disrupt maintenance planning. Strong access control, network segmentation, data integrity checks, and secure update procedures are therefore necessary, and the system should fail safely so that the loss of analytics does not compromise operation.

Logistics, Readiness, and Economic Implications:

The benefits of predictive maintenance reach well beyond individual machines. Accurate forecasts of component condition allow logistics organisations to position spare parts where and when they will be needed, reducing both shortages and excess inventory. They help planners schedule work during planned availabilities rather than interrupting operations. For deployed ships, early warning allows crews to prepare repairs, request parts in advance, or modify operations to reduce stress on a degrading component. Readiness effects are significant. By reducing unplanned downtime and avoiding failures at critical moments, predictive maintenance raises the proportion of the fleet available for tasking. Mobley noted that moving from reactive to predictive approaches typically reduces unscheduled outages and extends the time between overhauls, since maintenance is performed according to need rather than arbitrary interval (Mobley, 2002). In naval terms, this means more days at sea with confidence in the reliability of ships. Economically, the picture is nuanced. Savings arise from avoided failures, reduced unnecessary replacements, lower emergency repair costs, and better use of labour and parts. Against these must be set the costs of sensors, data infrastructure, software, integration, training, and ongoing model maintenance. Returns tend to be greatest for expensive, critical, and failure prone components where condition information is available, and smaller for cheap items that are simpler to replace on schedule. A portfolio approach that targets high value systems first is therefore sensible. Contracting arrangements also

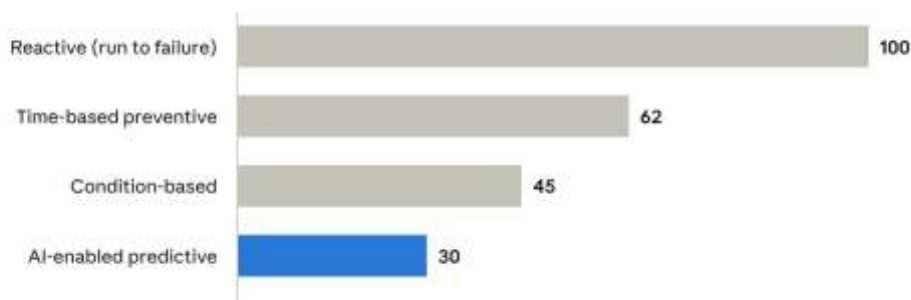
matter. Where industry holds maintenance data or performs support under performance based contracts, data access and sharing rules determine whether navies can exploit analytics fully. Navies increasingly seek data rights and open architectures to avoid dependence on single suppliers, while industry provides expertise in analytics and equipment knowledge. Collaborative models, with clear agreements on data ownership and security, can combine strengths.

Future Directions and Recommendations:

Several developments will shape the future of artificial intelligence in naval maintenance. Advances in sensor technology will provide richer data at lower cost. Transfer learning and federated learning may allow models to benefit from experience across ships and fleets without centralising sensitive data. Physics informed machine learning, which embeds engineering knowledge in learning algorithms, promises more robust models in data scarce settings. Autonomous inspection by drones and robots may supplement fixed sensors. Explainable artificial intelligence will become more important as organisations seek to understand and trust predictions. Generative and language based tools may assist technicians by retrieving maintenance histories and procedures. At the same time, adversaries may attempt to manipulate data or models, which makes robustness and security central research topics. Several recommendations follow. First, naval organisations should start with clear use cases linked to operational priorities, focusing on systems where failure is costly and data are available. Second, they should invest in data foundations, including sensors, standardised collection, curation, and governance. Third, they should validate models rigorously on representative data and monitor their performance over time. Fourth, they should integrate predictive tools into maintenance and logistics workflows and train personnel to use them with appropriate trust. Fifth, they should embed cybersecurity and resilience from the outset, assuring that systems can operate safely when analytics are unavailable. Sixth, they should adopt acquisition practices that secure data rights and open interfaces. The lesson of the literature is that predictive maintenance succeeds as a socio technical system in which data, algorithms, people, and processes are developed together (Lee et al., 2015).

AI-enabled predictive maintenance cuts unplanned downtime most

Illustrative unplanned downtime index; reactive maintenance set to 100



Summary:

This article has examined the applications of artificial intelligence in predictive maintenance of naval engineering systems. Naval machinery operates in demanding conditions, far from support, and with high reliability requirements, which makes traditional maintenance strategies costly and imperfect. Predictive maintenance, enabled by condition monitoring data and machine learning methods for fault detection, diagnosis, and prognosis, can detect degradation early and schedule interventions according to need. Applications span propulsion plants, electrical power systems, auxiliary machinery, and structures, and digital twins and integrated health management systems extend these capabilities to platform and fleet levels. Challenges include data quality, model validity, human acceptance, and cybersecurity. When implemented with rigorous validation, secure design, and integration into logistics, predictive maintenance can raise readiness, reduce unplanned downtime, and improve the use of resources. Navies that treat it as a long term capability, combining data, models, people, and processes, are best placed to realise its benefits.

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