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The benefits and opportunities of

Data-Driven Condition Based Maintenance

Digital Transformation Research Programme

Contents

Executive Summary

Timely and effective maintenance of seagoing vessels is fundamental to the maritime industry's core business of transporting cargo from A to B as safely and efficiently as possible. Well-maintained ships experience fewer unexpected failures or breakdowns, reducing the potential for accidents, delays and disruptions, while safeguarding the lives of the crews serving onboard.

While vessel maintenance necessarily incurs costs, careful asset management should ultimately lead to savings by preventing more expensive repairs or replacements that could result from neglect or deferred action. Effective maintenance can also help to improve fuel efficiency and reduce other operational expenses by allowing the ship to sail in condition as close to optimal as possible, creating benefits for both the shipping company and the environment.

The evolution of condition-based maintenance (CBM) has helped to increase the effectiveness of vessel care processes, moving away from a reliance on averages and statistical assumptions to an approach tailored specifically to the equipment or asset being maintained. Scheduling maintenance activities based on the actual condition of the equipment, rather than following a fixed calendar-based timetable, allows for resources to be deployed more efficiently and for the impact of maintenance procedures on vessel operations to be minimised.

Introducing and operating an effective set of CBM processes at a modern shipping company can be challenging, but the adoption of analytics-driven methods can have a significant impact in delivering evidence-based change and creating a clear path to improvements in the dependability and efficiency of the merchant fleet.

This report aims to provide an overview of how data-driven condition based maintenance (DCBM) processes, utilising the latest analytical models, can help to deliver these benefits to the maritime industry, outlining the challenges that need to be overcome and suggesting potential paths to successful implementation.

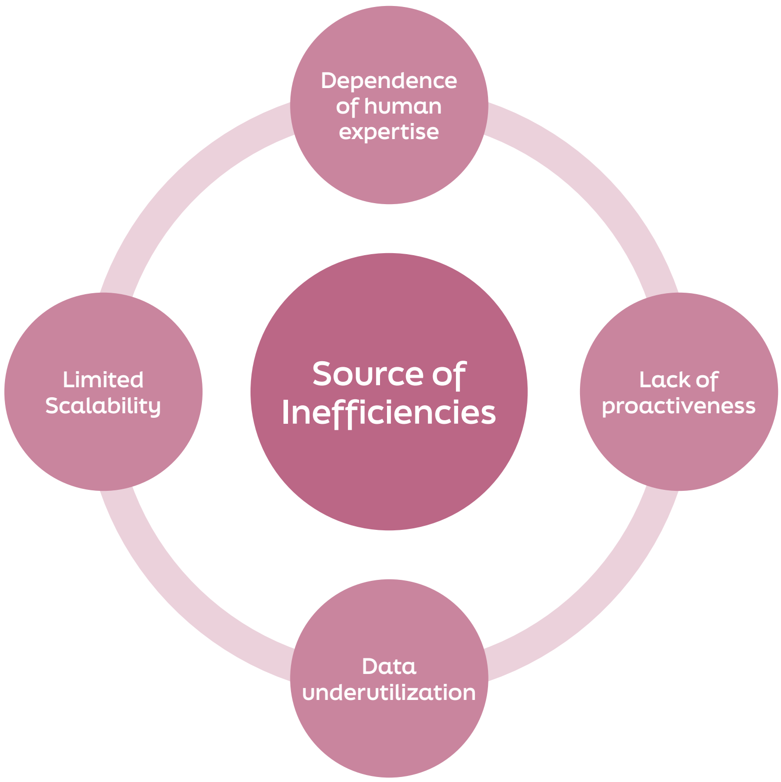
Common shipboard maintenance methodologies

Current maintenance practices within the shipping industry typically involve a range of common processes and requirements that present significant opportunities for optimisation.

Multiple stakeholders, including ship owners, classification societies and equipment manufacturers, all have a role to play in managing maintenance, but processes suffer from a lack of direct integration between the parties, exacerbated by the absence of shared common data platforms.

Despite the growing availability of data from modern vessels, this resource is often underutilised due to the lack of an integrated strategy among stakeholders, who often independently accumulate vast amounts of data without a clear plan for applying that data in conjunction with their partners in a way that creates synergistic benefits. This lack of integration also limits the scalability of traditional analytics methods, requiring extensive oversight from classification societies to ensure fleet-wide compliance.

Current practices that do not take advantage of available data regarding equipment status are consequently likely to remain inefficient, leading to both over-maintenance and under-maintenance, both of which carry their own cost implications. These legacy processes are also heavily dependent on the variable skill levels of human personnel, lack a proactive planning capability for future improvements, and will frequently result in unscheduled downtime that disrupts operational capabilities.



Condition-Based Maintenance (CBM) – A traditional approach

Scheduled Inspections
Traditionally, vessel maintenance has primarily followed a programme of scheduled inspections on dates chosen by classification societies to ensure that ships comply with international regulations. These inspections are often based on calendar time or usage metrics, such as running hours. During scheduled inspections engineers will manually examine machinery and systems to assess their condition.

Subjective Assessments
This manual process involves human experts assessing the condition of shipboard machinery based on their own training and experience, evaluating factors such as noise, vibration, temperature, and visual indicators to create reports for classification societies to use to determine compliance. These assessments are highly reliant on individual skill levels.

Reactive Maintenance
In many cases, maintenance on ships is conducted on a reactive basis, rather than being proactive. Reactive maintenance usually occurs when equipment shows signs of failure and may require the manufacturer's input on which parts and procedures are necessary to complete the process. When a system fails or shows signs of impending failure, immediate action then will be required to repair or replace the malfunctioning component. This approach can lead to downtime and increased operational costs.

Limited Use of Sensor Data
Some modern shipboard equipment will incorporate sensors, provided by the manufacturer or installed by the vessel operator, which can monitor key parameters such as temperature, pressure, and RPM. However, where such data is available it is often underutilised. Sensors may be applied to trigger alarms for out-of-range conditions, for example, but are rarely integrated into a comprehensive maintenance strategy.

Documentation and Record-Keeping
Classification societies require comprehensive documentation and record-keeping to ensure compliance with maintenance procedures, a process that usually needs to be managed by the ship owner or manager themselves. Manual logs and paper-based reports are still commonly used to document all maintenance activities, inspection results and repair histories, which are prone to human error and do not readily support data analysis or the development of predictive maintenance strategies.

Data-driven condition based maintenance (DCBM)

The maritime sector undoubtedly faces a range of challenges, both technical and structural, in deploying efficient and effective condition-based maintenance systems. However, many of these challenges could be substantially alleviated by integrating data and analytics-driven methods into the maintenance workflow and creating a data-driven condition based maintenance (DCBM) process.

By integrating data analytics with traditional maintenance methods, the industry has the potential to significantly improve both the reliability and operational efficiency of marine vessels. This will require the development of analytics-based diagnostic systems, real-time monitoring solutions, and comprehensive digital platforms to remove errors and inefficiencies from traditional processes and optimise workflows.

Presented below are four key challenges that have been identified in current condition-based maintenance practices, along with potential improvements that could be created through the application of an analytics-driven approach.

Four key challenges of condition based maintenance

Imprecise Maintenance and Inspection Protocols

The challenge: A fundamental issue with current CBM processes is a lack of precision in maintenance and inspection checklists, which often suffer from either an excessive number of included tasks or an absence of crucial maintenance activities. These shortcomings can create unnecessary added labour costs but also increase the likelihood of errors during maintenance. Furthermore, they can result in unexpected faults if essential upkeep steps are neglected.

Data-driven improvement: These challenges could be mitigated by an analytics-driven approach using historical and current operational data to revise and refine maintenance and inspection schedules. Implementing such a strategy would necessitate the creation of analytics-based diagnostic systems incorporating advanced diagnostic algorithms and precise measurement tools.

Deviations from Scheduled Maintenance and Inspections

The challenge: Another common issue in maintenance effectiveness is a frequent disregard for prescribed maintenance and inspection timelines. A failure to correctly follow suggested scheduled maintenance timings is often a primary causal factor in unexpected system failures.

Data-driven improvement: An analytics-driven remedy for this issue would be the implementation of digital platforms to accurately record maintenance activities. This could be completed in stages where complete automation of specific processes is currently impractical.

Accuracy in Condition Assessment

The challenge: The success of CBM can be compromised if the criteria used to identify hazardous operating conditions are vague or undefined, or if essential diagnostic data is scarce. These types of information gaps often culminate in operational failures and could lead to significant injuries if delays occur in identifying malfunctioning equipment.

Data-driven improvement: Analytics-driven methods can alleviate these issues by employing data analysis to uncover trends or early warning signs of unsafe operating conditions and potential system failures. To put this data into action, operators need to develop analytics-based systems that include diagnostic algorithms as well as appropriate instruments of measurement.

Insufficient Troubleshooting Response

The challenge: A lack of an effective response strategy outlining steps to take when faced with system failures can lead to delays in initiating required corrective actions and could lead to significant injuries.

Data-driven improvement: This white paper does not recommend a specific analytics-driven solution for this particular challenge, but the authors note that there is an urgent need for additional research and development in this domain.

A summary of all of these challenges, with potential improvement paths incorporating DCBM, is presented below.

Problem Category	Problem Details	Resulting issues	Data-driven improvement plans	Action required
Inadequate timing of maintenance and inspection activities	Unnecessarily excessive maintenance and inspection activities.	Increased labour requirement. Increased cost. Increased risk of maintenance errors.	Update the optimal maintenance and inspection schedule by analysing operational data and maintenance history.	Development of data-based condition diagnosis methods (using applied diagnostic logic, measurement devices).
	Required maintenance and inspections not carried out, or frequency is insufficient.	Fault occurs.	Update the optimal maintenance and inspection schedule by analysing operational data and maintenance history. Monitoring of operational data will allow detection of abnormalities and prompt early action even if scheduled maintenance frequency is insufficient.	Development of data-based condition diagnosis methods (using applied diagnostic logic, measurement devices).
Failure to perform maintenance and inspections	The listed maintenance activities and recommended frequency are not complied with.	Fault occurs.	Digital data-based management of maintenance requirements (with manual input where automation is impractical).	
Failure to accurately diagnose condition	Criteria for determining inappropriate (high risk) operating conditions are unclear.	Failure caused by improper operation.		
	Necessary diagnostic methods and techniques are not properly understood. Data necessary for diagnosis may be lacking.	Failure caused by improper operation.	Analyse operational data to detect inappropriate operating conditions.	Development of data-based condition diagnosis methods (using applied diagnostic logic, measurement devices).
	Delayed detection of occurrence of a failure.	Severe injury due to delayed detection of malfunction. Root cause of malfunction cannot be detected and corrected.	Enable early detection of malfunctions through analysis of operational data.	Development of data-based condition diagnosis methods (using applied diagnostic logic, measurement devices).
Failure to respond to breakdowns	Appropriate response to malfunctions has not been defined.	Severe injury due to delayed breakdown response.		

Evolving technologies for modern analytics

Until recently, the adoption of DCBM processes has typically been the preserve of a specialised niche of organisations within the aerospace and defence sectors. However, modern advancements in technology have served to make these systems more accessible to a wider range of industries than ever before.

Since the 1970s, the aerospace industry has employed a series of emerging technologies to increase reliability, reduce failures and optimise maintenance. With a more diverse fleet of assets and ownership, the marine industry is yet to adopt similar processes at scale, however technological advances and the wider availability of operational data are expected to drive significant improvements in this area.

Those early aerospace and defence adopters built their systems on proprietary algorithms, utilising software and hardware engineered by dedicated subject matter experts using company-specific (and IP protected) engineering tools. Developing DCBM systems at that time required expensive expertise and custom technology tools that put similar ambitions out of reach for most companies.

Today, many of those barriers have been eroded, with mainstream providers such as Ansys, Areva and MathWorks providing the engineering and software engineering services required, including open-source code libraries and developer tool kits that allow companies to re-use and build upon the work already done by external third parties.

In addition, a number of standards, handbooks and guidelines have been published that provide access to many of the different engineering approaches in hardware, software and systems that are required to successfully deploy DCBM. As a result, no team or company needs to start from scratch, and many of the activities that previously required highly specialised expertise are much more accessible.

The difficulty and expense of developing a DCBM infrastructure is expected to continue to reduce in the future, already demonstrated by the fact that some of the simpler DCBM applications (e.g. for rotating equipment) have spawned marketplaces that allow users to buy and integrate third party systems from providers such as Siemens, ABB and GE.

Five of the key recent technological advancements supporting this expanding access to DCBM systems include:

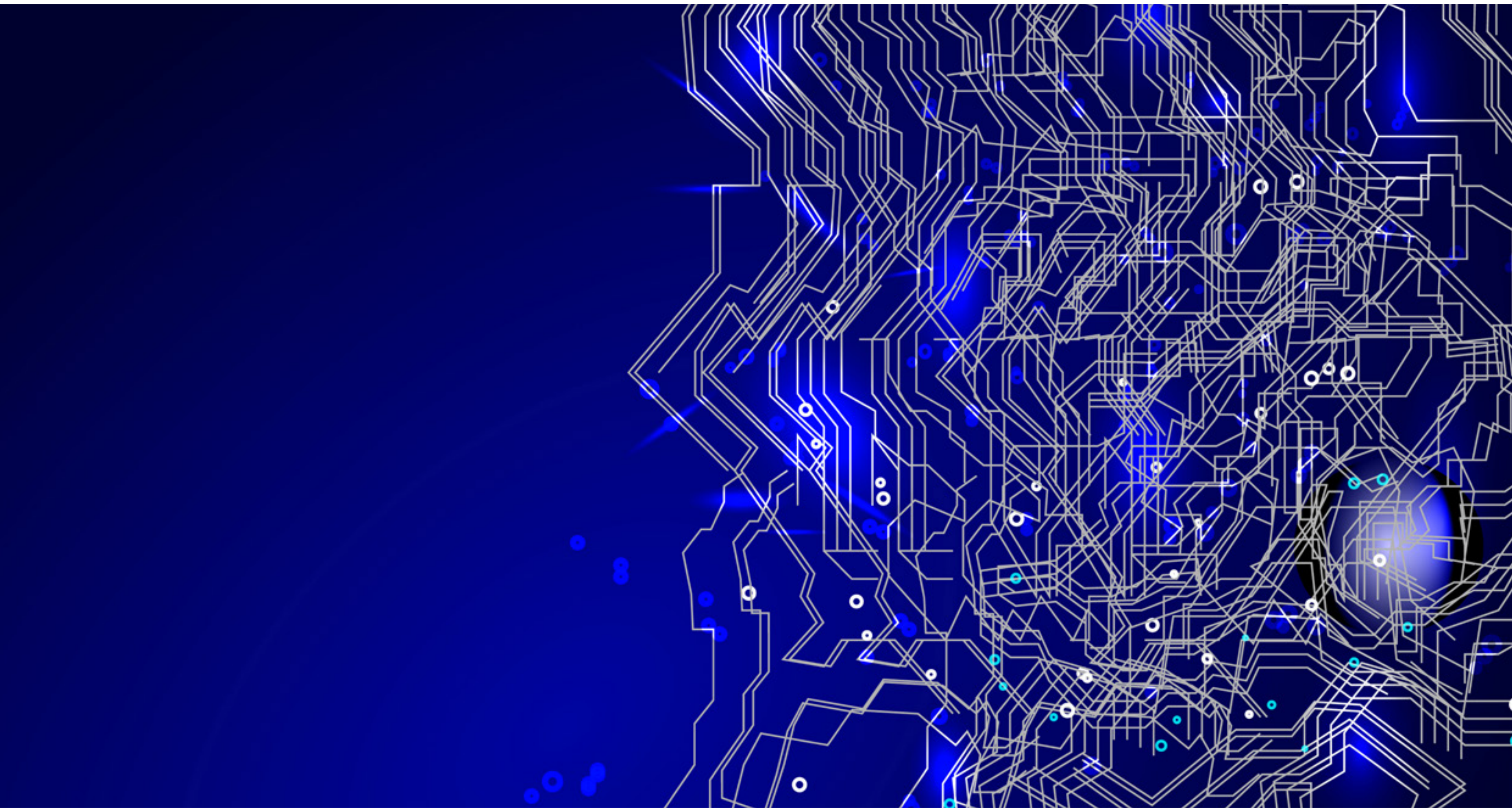
Connectivity – The availability of technology to support the collation and transmission of large volumes of digital data in maritime has become the norm in recent years, as had previously been the case with the aviation industry. This allows for comparative analysis at a depth and breadth not previously practicable and opens the door for alternative approaches to be explored.

Sensors – Equipment is now more commonly provided with sensors embedded as standard, improving the availability and reliability of maritime data. Advanced sensors may also contain computing elements to analyse outputs and further improve data quality, allowing greater confidence in the analysis delivered.

Edge computing – Increased access to edge computing devices offers the capability to process data at source with reduced latency, allowing for real-time analytics on connected and disparate systems without external connectivity. This makes it possible to take immediate action based on data insights.

Data Quality – Sophisticated data cleaning and integration tools have created significant advances in data quality, allowing organisations to improve their ability to aggregate data from various sources, including legacy systems, and create unified datasets for analysis.

Human-Machine interfaces – The role of human expertise in maintenance analytics is still crucial. Combining human knowledge with machine-generated insights can allow maintenance teams to combine the benefits of both worlds to make informed decisions.



Lessons from aviation

Maritime should take the opportunity to learn lessons from the past experiences of the aviation industry in its evolution of maintenance procedures, where previous calendar-based inspection and maintenance regimes have now transitioned to prognostic decision-making based on collation and analysis of data. This has resulted in a reported reduction in required inspection tasks while reducing the incidence and severity of unexpected failures.

Advancement of Monitoring Technology

1970s

Exceedance recording
Temp, RPM, Vibes

Detection of exceedance events (Anomaly Detection

1980s

Damage accumulation, Remaining Useful Life (post flight calculation)
Temp, RPM, Throttle position

Goal: reduce uncertainty and retain conservatism in estimating component life limit
Method: rainflow cycle counting, limits monitoring

Health and usage monitoring (HUMs systems) “lifing algorithms, usage counting algorithms, L10 algorithms, other variants”

1990s

Digital Fuel Controls

Engine data collection

Condition Monitoring

Fault Detection and Isolation (Diagnosis)

Prognosis – time to failure, recommended maintenance action

Goal: Extend time between overhauls by automatically detecting incipient failures in real time with embedded sensors
Method: vibration monitoring, oil debris detection, performance trending

2000s

Advance fault detection & isolation and diagnosis (physics based, models, machine learning, etc.)

2010-present

Prognostics and integrated health management (e.g. system digital twins, coupling with adaptive controllers

Machine Learning and Data-driven algorithms

In addition to the technological advancements listed above, the emergence of new data-driven algorithms and machine learning tools has also significantly widened potential access to DCBM, removing the need for direct specific knowledge of equipment health and causes of failure to be programmed into the system by software engineers.

Machine learning algorithms can be built by 'learning' from data sets that are representative of different operating conditions – such as 'normal', 'abnormal', 'faulty' and 'failure'. These algorithms can incorporate monitoring and reasoning capabilities that allow the software to recognise the status of the equipment and the condition of its various parts based on observed operational data.

The ability to implement data-driven algorithms has been made possible by several recent commercial and technological advancements, such as the development and commercialisation of foundational models like Generative Pre-Trained Transformers (GPTs) that are capable of a level of reasoning, analysis and decision making (even creativity) not seen in previous machine learning systems. These next-generation machine learning algorithms are also designed to be able to operate across multiple applications and use cases rather than specialising in specific tasks.

The costs associated with the development of machine learning models has also drastically reduced. In the past, data-driven algorithms were kept proprietary given the expertise, custom computing technology and high costs involved in their development. Today, developer communities, technology companies and organisations such as NASA provide public access to data-driven algorithms, including their source code libraries, to the extent that open-source algorithms are now available at zero cost in some cases.

The cost of the computing power and memory required to run machine learning models has also reduced dramatically in recent years. The emergence of cloud computing has eased the capital costs for businesses looking to develop high performance computing facilities, while continued innovation in graphical processing units (GPUs) has accelerated computational capabilities, reducing the model training time required.

For those that are new to the field of data-driven algorithms, a group that will include most maritime organisations, ongoing standardisation and automation efforts in the sector are helping to remove some of the barriers to entry when it comes to the engineering, production and deployment of these tools.

Various ML Ops (Machine Learning Operations) frameworks are available, supported by ISO and IEC standards, to assist companies in building competence in the application of data-driven algorithms, while additional ML DevOps (Machine Learning Development and Operationalisation) frameworks and tools are available from engineering focused providers delivering services for the advanced monitoring of equipment and systems.

Leveraging these resources can reduce the engineering burden for new users of these technologies by providing proven monitoring-specific examples that can be adapted for maritime use, such as anomaly detection algorithms that can be customised to specific monitoring use-cases.

A list of technologies and tools to support the development of data-driven algorithms and machine learning models is provided in Annex 1

Industry drivers for data-driven maintenance

The potential benefits from the enhancement of shipping maintenance through the application of data also align closely with several macro-level change drivers that are currently reshaping the maritime industry, pushing shipping companies to adapt their operational processes to stay competitive, improve efficiency, and meet evolving demands.

A combination of economic, regulatory, technological and competitive factors will require the shipping sector to continue to evolve in its approach to vessel management, with data-driven maintenance likely to play an increasingly important role in ensuring that improved levels of reliability, safety, and sustainability in maritime operations are achieved going forward.

Macro-level maritime change drivers

Cost Efficiency and Profitability: Shipping companies are under constant pressure to reduce operational costs and improve profitability. Data-driven maintenance helps to optimise maintenance spending by reducing the number of inspection, survey and functional testing tasks required, allowing resources to be to be focused on carrying out required maintenance at the optimal time, minimising unplanned downtime and improving operational flexibility.

Environmental Regulations: With global goals to reduce emissions driving requirements for more efficient vessel operations, data-driven maintenance can help to reduce fuel consumption and emissions by supporting greater efficiency in the operation of machinery, while avoiding the performance of maintenance at inefficient times.

Optimised maintenance can also help to reduce the carbon footprint of the spare parts and maintenance logistics activities required to service a vessel. Traditional planned maintenance typically results in the provision and storage of a large number of spare parts, some of which often remain unused beyond their expiry date. Optimised maintenance schedules will also minimise travel hours for service engineers and technical personnel attending to equipment and systems for testing and troubleshooting.

Safety and Risk Mitigation: The increasing public visibility of incidents that occur at sea, and the consequent risks they carry for company reputations, mean that maritime operators can benefit from being seen to be adopting the latest technologies to enhance equipment safety. DCBM sits firmly within that category, helping to identify and address potential safety risks by proactively managing equipment health and reducing the likelihood of unscheduled downtime and failures.

Regulators and insurers are also showing an increasing interest in data-driven maintenance procedures as a means of providing transparency in compliance processes and reducing the risk of failures in service, delivering improved confidence in vessel operations and a reduction in insurance claims.

As DCBM allows for the creation of more precise and adaptive risk models than traditional approaches by continuously collecting and analysing data from various ship systems, the application of data-driven methodologies within the maritime industry could deliver far-reaching benefits beyond merely ensuring safe operations.

Improved digitalisation would support the accelerated adoption of parallel technologies that could improve operational efficiency and enable decarbonisation, such as the utilisation of 'digital twin' models to identify new opportunities for cost and fuel reduction.

This could create savings that are similar to, if not better than those realised by early adopting industries like aviation – where US Army and FAA sources have reported that data-driven condition-based maintenance regimes for aero engines have delivered a 30% reduction in mission aborts, a 30% reduction in maintenance costs and a 5-10% reduction in scheduled maintenance costs.

The interconnected nature of the maritime industry requires significant collaboration among different actors to achieve the various benefits discussed above. These stakeholders can be classified within the following categories, which will be explored in more detail below:

- Ship Owners / Operators
- Classification Societies / Regulators
- Technology Providers (including OEMs – Original Equipment Manufacturers)
- Cargo Owners
- Insurance Providers
- Financial Services

Drivers for ship owners and operators

Vessel owners and operators clearly stand to gain from optimised asset utilisation, through increased equipment availability, reduced downtime and lower total maintenance costs, which collectively contribute to a higher return on investment from their assets.

Safety is a major driver, and the adoption of proactive measures in maintaining vessels will support the early detection of abnormalities, preventing major breakdowns and enabling flexible maintenance planning not constrained by the methods commonly found in Traditional Breakdown Maintenance (TBM) and Condition Monitoring Systems (CMS). DCBM can be expected to not only reduce the frequency of maintenance activities, but to also significantly lower operational expenditure (OPEX) and crew workload.

The increase in overall availability of the vessel, which can be predicted with a higher level of certainty through analysis of actual operating conditions for each particular system that is dependent on components that are subject to degradation over time, is a key consideration for owners when building a business case to demonstrate return on investment in DCBM technologies.

Some of the key benefits in this area can be delivered through management of the uptime or availability of different 'functions' of the ship, rather than individual components in isolation – for example, is the 'navigational function' available for operation, or the 'loading'?

This approach requires consideration of the ship as a 'system of systems' that undertakes a range of connected functions, which each involve a certain collection of components that are required to dependably work together.

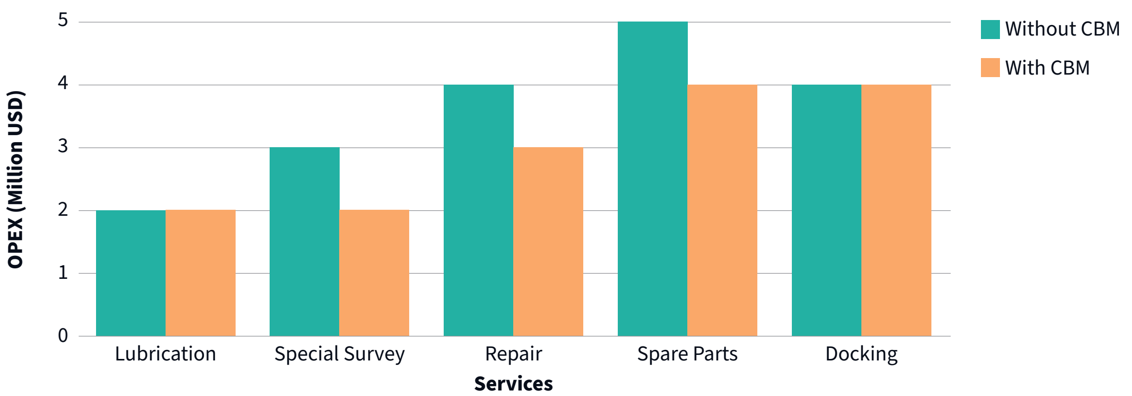
The level of digitalisation of such systems will determine the success of the adoption of data-driven decision-making business models, and is dependent on a number of factors – including the maturity of the available technology, the cost of adapting the technology to specific requirements, the actual adoption of the technology on board real ships, and the acceptance of the analysis provided in the operational decision-making process (supervised by humans in the initial stages).

Real-life OPEX benefits of Condition-Based Maintenance

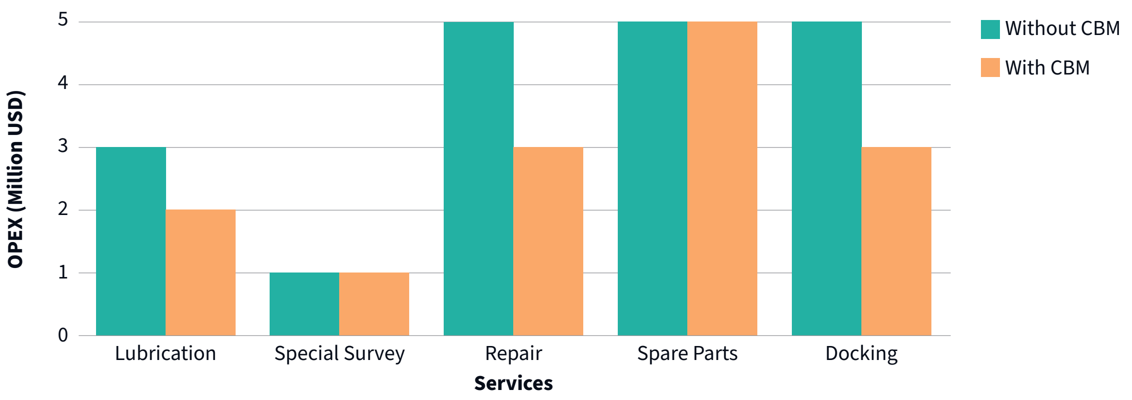
Among all of the related stakeholder categories, the incentive for shipping companies to adopt DCBM processes may be the easiest to quantify, as reduced maintenance spending can be directly expressed as dollar amounts.

To highlight this point, the below data has been collected from operating vessels in a shipping company fleet, from ships that have deployed CBM processes and those that have not. The vessels have been split into categories based on their number of years in service, with the cost areas (OPEX) directly impacted by the adoption of CBM methods similarly classified by type.

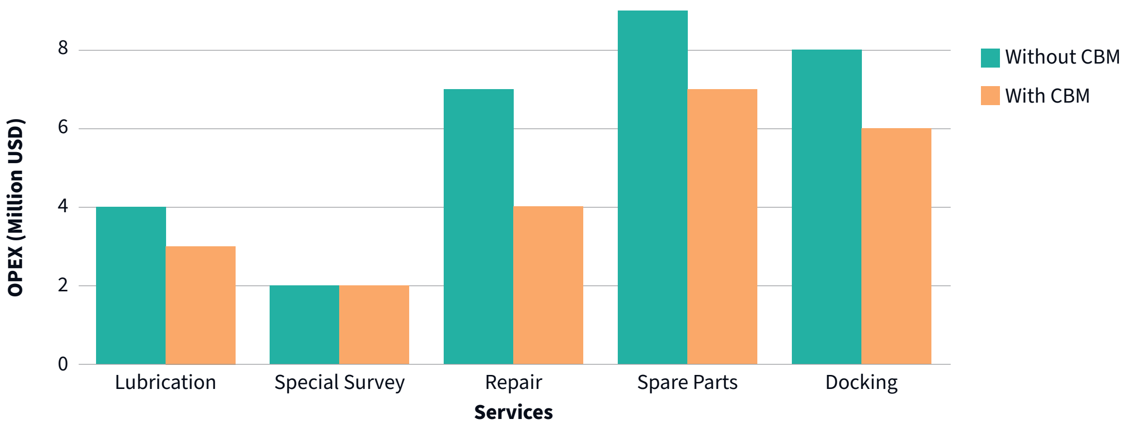
OPEX Comparison for 5 Years in Service with and without CBM



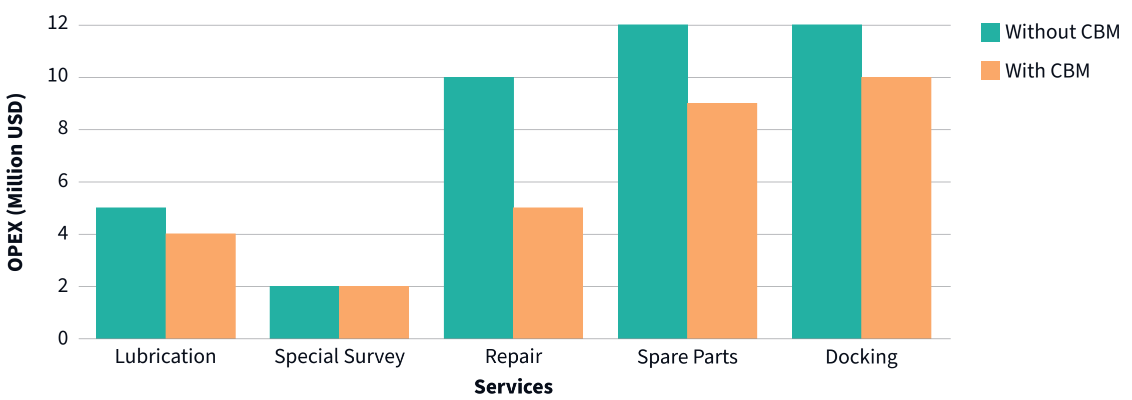
OPEX Comparison for 10 Years in Service with and without CBM



OPEX Comparison for 15 Years in Service with and without CBM



OPEX Comparison for 20 Years in Service with and without CBM



This real-world data clearly illustrates the disparities in maintenance costs between vessels utilising CBM and those without CBM – across all service categories and years of service, vessels implementing CBM consistently demonstrate lower OPEX compared to their counterparts.

Over the years, the cumulative savings that could be accrued by vessels employing CBM become increasingly evident. Notably, the gap in maintenance costs widens with the age of the ship, underscoring the long-term financial benefits of CBM adoption. While certain services exhibit more pronounced cost reductions from CBM implementation, others showcase moderate to significant savings, contributing to overall fleet-wide cost optimisation.

The data underscores the tangible benefits that can be created through the integration of Condition-Based Maintenance strategies within the operational framework of a shipping fleet. By leveraging predictive maintenance techniques and real-time monitoring, organisations stand to significantly mitigate maintenance expenditure, enhance operational efficiency, and prolong asset lifespan.

Drivers for other stakeholder groups

Other stakeholder groups within the maritime sector also stand to benefit from the adoption of DCBM techniques, with their individual drivers varying based on their interaction with vessel operators and with one another.

Classification Societies – For classification societies, one of the most significant potential benefits of an industry shift towards DCBM is the ability to develop more accurate and dynamic risk models, which would facilitate targeted inspections with more efficiently allocated inspection resources, as well as a streamlined certification process delivering a comprehensive, data-backed overview of the condition of maritime assets.

By adopting a proactive, evidence-based strategy incorporating actual vessel data, class societies can create greater transparency in their assessment criteria and further increase the credibility of their methodologies with regulatory agencies. In addition, the insights gathered from data analysis can be used to update classification rules and guidelines to more closely align with actual operating conditions, increasing their relevance in a dynamic maritime environment.

Original Equipment Manufacturers (OEMs) – OEMs stand to benefit from the implementation of DCBM through access to a greater lever of granular data from the improved digitalisation of vessel systems, allowing those manufacturers to access more detailed equipment performance metrics to support innovation in design improvements at a level far exceeding current industry standards.

Equipment providers could also offer a higher level of customisation to customers in their maintenance plans, with timelines based on operational use. This could lead to increased sales of spares for installation before a failure occurs and reduce the likelihood of non-original spare parts being purchased, or third-party service providers being employed for maintenance management.

OEMs could create better informed warranty contracts based on the use of machinery if equipment follows a DCBM methodology, and make evidence-backed predictions when discussing the reliability and operational lifecycle of the equipment. Manufacturers would also be in a better position to predict spare parts and servicing requirements across the customer base by making calculations using actual machinery reliability and usage data, reducing the cost of providing such services and the expense of associated logistics.

The time and cost involved in carrying out repair services would also be reduced if the nature of a failure or issue can be more readily identified, with the complexity of specific repairs analysed and used to improve processes so that the effectiveness and efficiency of maintenance efforts can be benchmarked.

Increases in sales volume could result from improved design capabilities, particularly incorporating changes demonstrated to create higher reliability based on customers' operational and failures data. The adoption of DCBM could also create the opportunity to offer proactive model maintenance services to asset owners as an additional option with value-added service packages. These kinds of value-added services could help OEMs transition from suppliers to partners, businesses that are demonstrably invested in their clients' long-term success.

Cargo Owners – The application of DCBM processes within the maritime sector could have a direct impact on cargo owners by providing a foundation for more transparent and collaborative relationships with other stakeholders, like ship owners or classification societies.

The data delivered can serve as an impartial basis for performance reviews, contract renewals, or even for identifying areas of shared investment to improve overall operational effectiveness. Reduced disruptions and penalties through improved reliability in vessel operations could also free up capital for cargo owners to invest in other areas of their business, such as research and development, marketing, or geographical expansion.

Insurance Providers – Insurers stand to significantly benefit from the adoption of data-driven management of the maintenance of equipment on ships by allowing insurance premiums to be calculated with more certainty, through the expansion of the pool of data available for use in their analysis of the risks involved. Access to a greater level of specific operational data from vessels would help these companies to reduce pay-outs for machinery failures and to optimise overall premiums.

Financial Services – Shipping financiers and the various banks and other organisations providing capital to maritime companies would be able to model their financial forecasts with greater certainty if given access to the increased volume of vessel operational data provided by DCBM. A greater understanding of the specifics of vessel operations will allow financial providers to make data-driven decisions on where to allocate their investments.

It is important to note that incorporating DCBM as an integral part of a comprehensive maritime operations ecosystem will not be achieved without overcoming significant challenges. The table below offers a summary of some of the key opportunities and challenges for a selection of the major stakeholders.

	Opportunity	Challenge
OEM	Expand sales of condition monitoring services.	Additional risk management capabilities needed.
	Increase in information collected, such as operational data and maintenance records, leading to better product development.	Additional labour resources needed for expanded DCBM operations.
	Increase in product value, promoting sales.	Potential reduction in revenue from component sales.
Class	Optimised operations can prevent occurrence of serious problems.	Additional risk management capabilities needed.
	Reduced frequency of inspectors visiting vessels.	New skillsets required for DCBM inspections.
Owner/Ship	Increased flexibility in maintenance implementation, leading to reduced maintenance costs and workload for crew members.	Cost and labour investment in new maintenance processes to share data, maintenance records, etc. with relevant stakeholders.
	Onboard systems are operated appropriately, preventing serious problems.	Improper operation may increase the risk of unexpected problems.

Implementing data-driven maintenance processes

Implementation of data-driven processes for ship maintenance has the potential to deliver transformative benefits for the maritime industry when compared with the limitations of current practices, impacting ship owners, classification societies, equipment manufacturers and a range of other stakeholders.

Enhanced predictive capabilities allow for pre-emptive maintenance activities to be carried out, significantly reducing downtime and operational costs, while the utilisation of resources can be optimised through the application of data analytics to allow ship owners to prioritise maintenance activities based on the likelihood and severity of potential failures.

This analytical insight would be invaluable for vessel operators in discussions with classification societies and equipment manufacturers to create more effective maintenance schedules. Ideally, predictive models could be created that align with the guidelines set by classification societies and incorporate best practices recommended by equipment manufacturers, providing the opportunity to standardise and scale maintenance operations across fleets.

Creating synergies between classification societies, ship owners and equipment manufacturers by integrating various data sources into a shared centralised ecosystem platform would enable a holistic approach to maintenance, ensuring better decision-making and overall maritime safety.

However, as mentioned in previous sections of this whitepaper, many challenges remain in implementing data driven condition-based maintenance processes in the maritime sector. The development of new data-based condition diagnosis methods (with applied diagnostic logic, and appropriate measurement equipment) in place of traditional practices will require commitment from multiple stakeholders, while applying DCBM will also necessitate investment in sensor technology to collect data from the asset of interest.

The integration of sensor technology and analysis instruments into maritime operations will require significant expenditure, both for initial setup and ongoing maintenance. This expense may also be compounded by a subsequent potential increase in monthly ship-to-shore communication charges for data transmission and monitoring. To create a scalable and sustainable business model, detailed cost analyses are essential, especially when tailoring solutions to specific use-cases.

Aside from the technical challenges, there is also a potential disconnect between Original Equipment Manufacturers (OEMs) and ship owners in their pathways towards effective DCBM, particularly when it comes to data collection units.

Many ship owners already possess their own data collection systems, which might not be compatible with OEM requirements to connect their own machinery. For OEMs to leverage these existing systems a set of industry standards for data collection and sharing needs to be established.

OEMs also require access to digital maintenance records to monitor spare parts usage for DCBM to be effectively implemented, which will require ship owners to prioritise digitisation of maintenance logs to facilitate data sharing and to streamline overall operational workflows.

Building a pathway to DCBM

Once a shipping company is committed to implementing DCBM, ideally in cooperation with its industry partners, there are three key areas that should be comprehensively analysed to make sure that value creation will be maximised – technology, methodology, and operational workflows.

Technology – Value can only be created from data-driven decision-making if it is based on accurate digital models that can replicate reality with a high level of fidelity. These models, or 'digital twins', should provide the basis for analysis that all parties can trust, so that decision-making accountability lies with the technology, not the human. The use of suitable modelling equipment, systems, and operating environments are all integral to the creation of value-creating data-driven business models.

Methodology – An effective DCBM process must be built on an operating model where data can be trusted to generate the desired business outcome. The critical key parameters for operation should be identified and then monitored and measured by digital models. At a basic level, this would include critical data such as equipment reliability, as well as the connectivity status of the machinery to allow data to be captured.

Operational workflows – There are a number of different options for interacting with the data collected, so a preferred operational workflow should be chosen that suits the company's specific requirements. This could involve sharing of datasets themselves with approved parties, or sharing of data outcomes with chosen partners that have been granted access to provide support in decision making processes.

Depending on which technology, methodology and operational workflows are adopted, there may be several implementation pathways that could be followed to create an effective DCBM process that will generate the outputs required to support improved maintenance decisions.

We envisage four potential pathways that may be practicable, depending on the companies involved and their own specific circumstances:

- Digitising and creating digital models of existing equipment.
- Utilising AI, based on machine learning that analyses testing data and operational data from the relevant equipment.
- Re-engineering current equipment designs to support high fidelity data collection and digital use cases.
- A hybrid pathway, consisting of the re-engineering of all or parts of equipment based on operational data to create a 'phygital' (physical and digital) model of the equipment. Data is shared, from design to operation, linked to a commercial contract and value sharing model.

It should be noted that value generation through DCBM can be multiplied by applying any of the above pathways to whole 'systems' rather than individual pieces of equipment – for example, creating a data-driven maintenance process pathway for the 'navigation system' as a whole, or the 'shafting system', the 'propulsion system' etc.

Designing a DCBM process

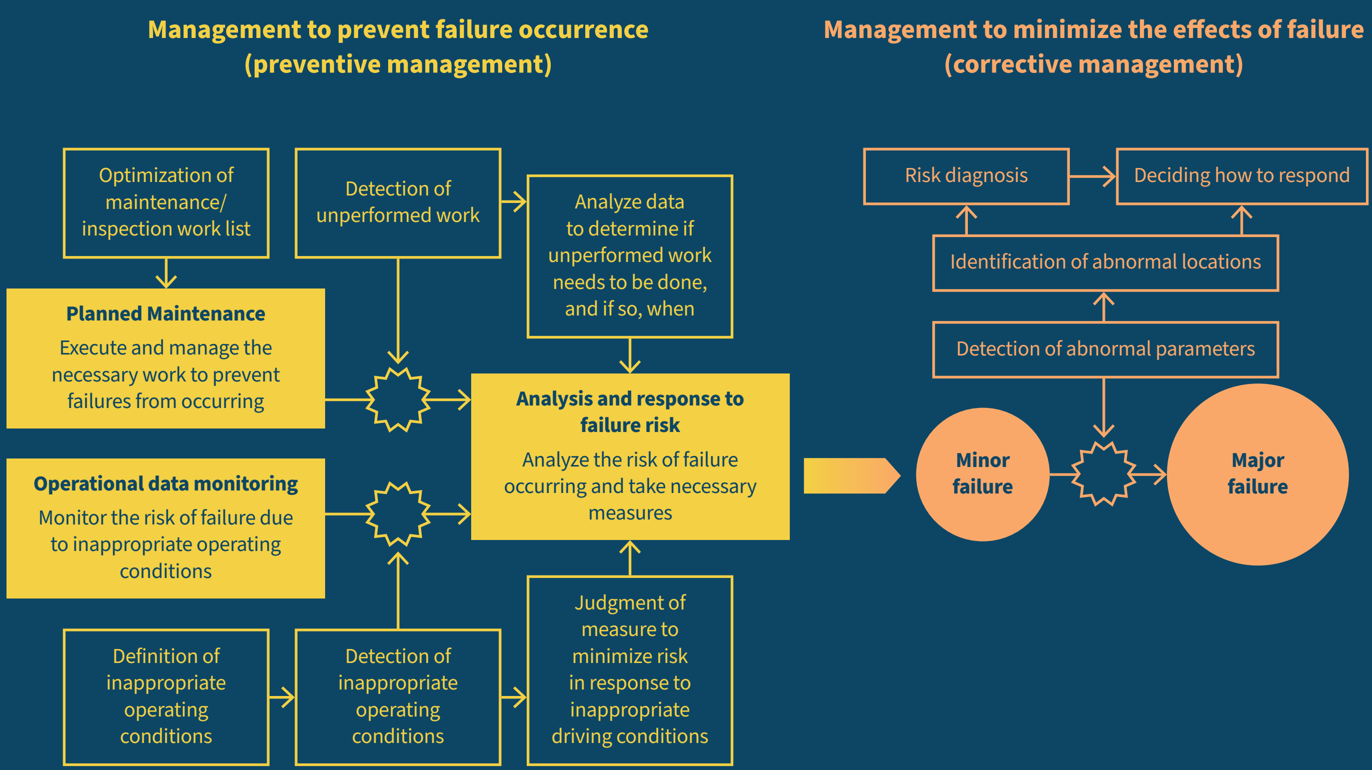
When it comes to designing a data-driven CBM process, there are typically two desired outcomes to choose from – proactive failure prevention, or failure minimisation. The type of strategies that will be followed will differ slightly in either case.

Strategies for Proactive Failure Prevention

- Establish Maintenance and Operational Guidelines: Develop clearly defined criteria for both the maintenance and operation of the equipment, aimed at averting system breakdowns and malfunctions.
- Identify Consequences of Non-Compliance: Clearly describe the adverse outcomes or major issues that may arise if the established guidelines are not followed.
- Create a Compliance Monitoring Framework: Implement a system to continuously monitor and assess adherence to maintenance and operational guidelines.
- Data Acquisition for Diagnostic Purposes: Collect comprehensive sets of data from vessels in operation that can be utilised for diagnostic evaluations of actual conditions.

Strategies for Failure Minimisation

- Confirm Anomaly Detection Logic: Develop algorithms or logic-based sequences to be used to promptly identify anomalies and determine their underlying causes.
- Systematise Anomaly Handling: Formalise the procedures and systems that will be used to deal with detected anomalies to ensure a standardised and effective response.
- Data Acquisition for Diagnostic Purposes: Accumulate comprehensive sets of operational data to facilitate precise and actionable diagnosis of issues.

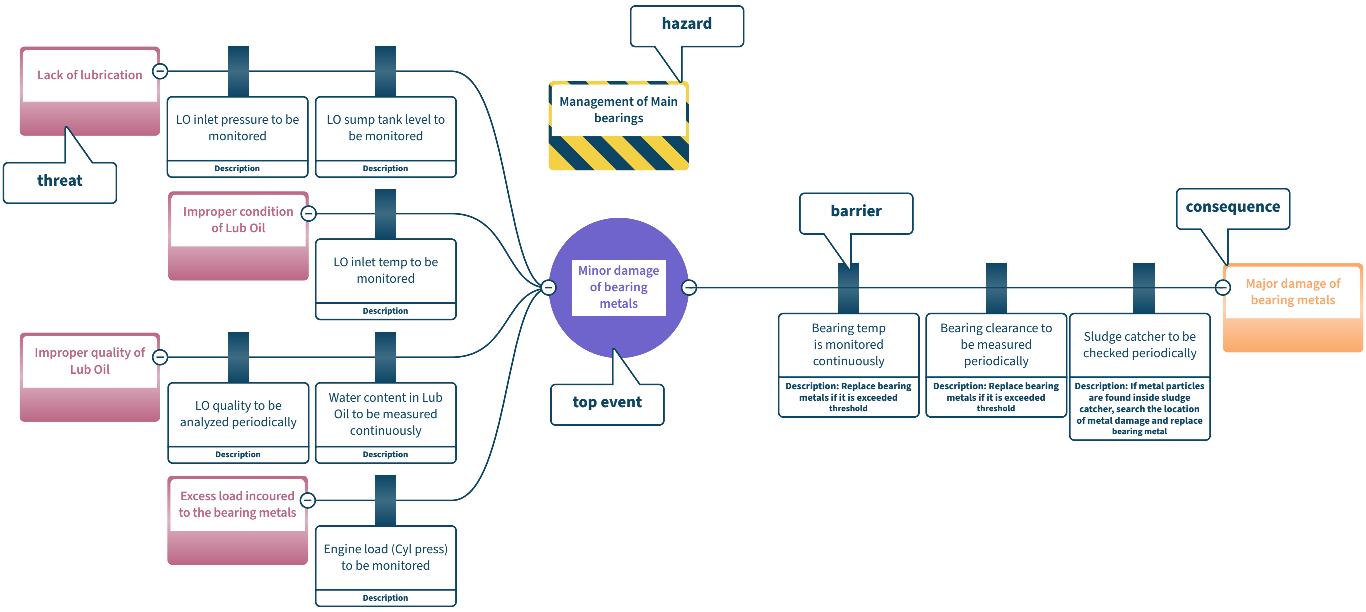


Communication and goal alignment

To develop a methodology that best fits as many use cases as possible for the relevant stakeholder groups, it is important to be able to discuss the DCBM process and develop a mutual understanding of how these methodologies can best be implemented for each organisation's particular objectives.

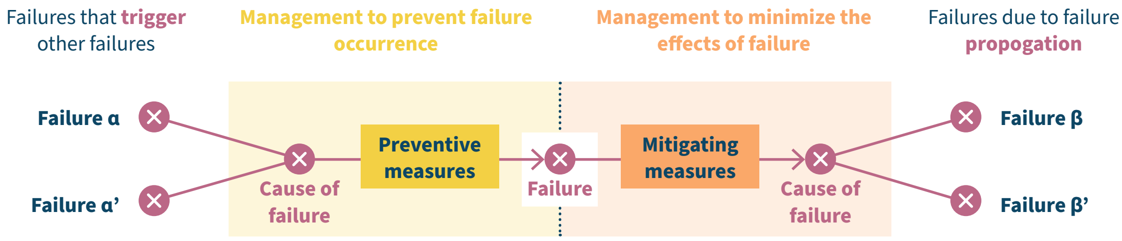
One way to design and communicate how value can be delivered from DCBM is to use risk-assessment tools such as the 'Bow-tie' model below. In this example, causes of failure (Threat) and preventive as well as mitigation actions (Barrier) can be analysed to determine how major failures that all parties want to avoid (Consequences) can be prevented.

Identified and agreed methods to neutralise Threats can be utilised in the development of the DCBM system, to improve procedures or to inform future changes in the design of the equipment itself.



In order to determine effective monitoring points and preventive measures, it is also necessary to understand the causes of failures and their risk of occurring. Performing a Failure Mode Effect Analysis (FMEA) as part of the DCBM design process is recommended, to properly organise preventive measures and anomaly detection methods that can be used for the various identified failure modes and potential causes of malfunction for the components.

Additional preventive measures and detection methods can be derived by quantifying risk within this process, which can then be utilised in the selection of the parameters to be monitored by the sensor, or other parameters such as sound or images that may indicate a failure.



Training machine learning models for DCBM

Development and training methods for the machine learning models and algorithms required to power data-driven CBM can be divided into four categories – supervised learning, unsupervised learning, reinforcement learning and semi-supervised learning.

The type of DCBM algorithm created is influenced by the availability of labelled input and output data sets, meaning inputs in the form of time series sensor data that can be matched with outputs that describe the state or condition of the equipment, as well as its sub-assemblies and replaceable parts (including failure modes).

Supervised learning algorithms explicitly require labelled time series data that corresponds to examples of 'normal', 'abnormal', 'faulty' and 'failure' conditions, with the algorithm's capabilities and performance directly influenced by the availability of multi-variate data sets.

From a fault detection and isolation perspective, this requires unique data sets that represent each different failure condition – if a piece of equipment has 100 unique failure modes, then unique time series data for each failure type should be made available for algorithm training.

However, in reality those required training data sets can be difficult to acquire, for a variety of reasons:

- **Lack of identifiable failure taxonomy for the candidate equipment.** Failure descriptions can be subjective if there are no formal templates and guidance for their identification. Incorrectly described failure modes, e.g. an incorrectly identified affected part, incorrect failure type or incomplete failure description, may be erroneously 'learned' by the data-driven algorithm, resulting in false positives or false negatives during deployment.

- **Exceeding minimum/maximum thresholds of sensors may not automatically mean a failure.** Similarly, incorrect labelling of events where thresholds are exceeded as being representative of failure within the training data, where that threshold breach is not a legitimate failure event, could result in false negatives or false positives.

- **Training data set imbalance.** While large data sets may be collected by local control systems (e.g. SCADA systems) and integrated control systems (e.g. propulsion management, SMS), most of these data sets are representative of normal operations with occasional instances of anomalous operations (e.g. exceedance events, intermittent faults, unexpected outliers). Very few cases of actual failure modes may be recorded within the data. Furthermore, the availability of training data sets that do include specific failures are typically a small subset of all potential failure modes.

- **Fault and failure complexity.** A complex piece of equipment could consist of several sub-assemblies and hundreds of replaceable parts. The operational and environmental stressors experienced by the system can trigger multiple faults with various causes that can progress to different failure modes. Capturing these data sets for training is impossible without a very clear failure taxonomy and precise labelling of faults and failures.

- **Big data is not representative of the diversity of the operational environment.** Having large data sets does not automatically deliver representative examples of 'normal', 'abnormal' and 'failure' operating conditions. A data driven algorithm will only learn from the unique examples in the training data that has been provided. This is one of the major reasons why consumer technology companies are at the forefront of data-driven algorithm/machine learning development, as the general public is constantly producing data at a scale that supports more accurate machine learning.

In contrast to the supervised learning process above, unsupervised learning algorithms automatically extract specified features (for anomaly detection, fault detection, diagnostics and prognostics) from the time series data presented and use that information to estimate and distinguish different states of health, which can then be labelled as outputs.

While unsupervised learning can be a powerful method for performing anomaly detection, it can face challenges if there are multiple failure modes that appear in isolation, or if there are different permutations and combinations that lead to the same failures in different cases.

DCBM functional architecture

Data-driven condition-based maintenance can deliver significant improvements in the safety, reliability and availability of assets. An example of a typical functional architecture to implement DCBM is described below:

1. Availability of Electronic Sensors (fitted as standard in some equipment)
2. Additional Sensors to improve Fault-Failure Observability
3. Sensor Data Validation (Data Quality Management)
4. Data Acquisition
5. Descriptors/Fault Feature Extraction
6. Anomaly Detection
7. Fault Detection and Isolation
8. Diagnostics
9. Prognostics
10. Equipment State of Health Advisory
11. Generation

Incentive alignment and new business models

For data-driven condition-based maintenance (DCBM) to be effective from an industry perspective, relevant interconnected stakeholders will need to make a move away from working with isolated systems and adopt integrated platforms. To motivate these stakeholders to implement these new ways of working it is important that the incentives of all parties involved are aligned, so that benefits accrue for all actors.

Close collaboration between stakeholders is essential in understanding the impact of DCBM and highlighting those benefits. Metrics should be established to evaluate the effectiveness of DCBM in delivering value to each of the parties involved, both quantitatively and qualitatively.

Examples of how value can be delivered when incentives are aligned can be seen in some early collaborative projects exploring potential DCBM pathways, where shipping companies, Original Equipment Manufacturers (OEMs) and class societies have already begun working together to explore specific demand-side use cases and make the relevant adjustments to match the capabilities of OEM technologies.[1,2]

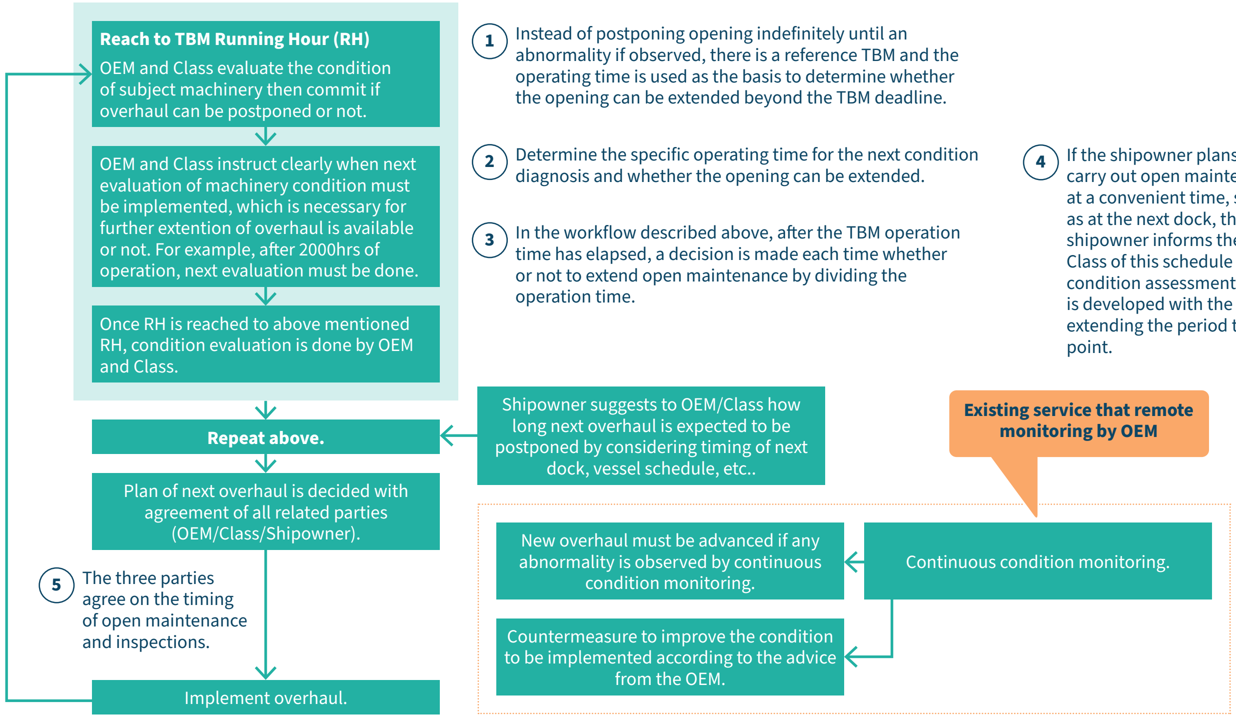
Small success stories like these can play a vital role in building confidence and trust in the DCBM concept, breaking down barriers to open collaboration and innovation by demonstrating how improvements can be achieved. This collaborative approach also enables consensus-building, scope coordination and capacity building, allowing partners to jointly develop new ways of working together for mutual benefit.

With the individual CBM systems typically offered by OEMs and other solution providers today, the burden of responsibility for operation and management still largely falls on the ship owner, which increases the risk of issues arising. To address these challenges, a more integrated data-driven CBM system is proposed (outlined in the diagram below).

This new approach, backed by class approval of DCBM methodologies, would provide an increased level of assurance for ship owners by providing data-backed evidence of a vessel's condition, which could then be further supported by Hull & Machinery (H&M) insurance coverage in case of unforeseen issues.

Additionally, this integrated multi-stakeholder DCBM approach would have the potential to reduce both planned and unplanned maintenance costs significantly. As a result, a more accurate return on investment (ROI) can be calculated for the different parties and the responsibilities of each actor defined, opening up a pathway to new business models for Original Equipment Manufacturers (OEMs) and transforming operational processes for both classification societies and ship owners.

1 NYK Group Joint Research on CBM Adopted in ClassNK Guidelines – https://www.nyk.com/english/news/2021/20210514_01.html
2 NYK pilots Wärtsilä predictive maintenance service – https://www.wartsila.com/jpn/media/local-news/13-04-2021-wartsilas-next-level-predictive-maintenance-service-can-lead-to-fleet-wide-implementation-by-japanese-shipping-group



Innovation in business models

The broader implementation of DCBM processes in shipping will require the creation and sharing of value across networks of digitally connected maritime stakeholders, at sea and on land. The scope of work required to maximise the value to be derived from DCBM will include the digitalisation of a different combination of: Selected Equipment; Selected Systems; Selected Functions; and Selected Value Chains.

An intermediate 'quick win' could involve the digitalisation of systems that are currently managed by software onboard ships, and/or systems with design characteristics that are already well defined, to the extent that they would support accurate measurement of their operational status.

One example of this would be the shafting system. Traditionally the condition of propeller shafts has been assessed by visual examination. This method has largely been replaced by remote examination based on available data, including oil analysis, bearing temperatures and measurement of wear, to reduce the need for withdrawal of the shaft.

Analysis of the data allows the company to determine the likelihood of deterioration of the shaft bearing having occurred, and whether further examination is required. However, this means that the issue is only addressed after the fact. DCBM, incorporating design parameters and operational data in conjunction with existing data sets, could deliver additional value by potentially identifying issues before damage occurs, enabling preventive measures to be taken.

'Routine' vs 'Radical' innovation

While use cases like those described in this paper might be categorised as innovative models within a maritime context, they represent an incremental level of innovation from the way we operate today rather than a radical shift. According to a June 2015 Harvard Business Review (HBR) paper titled 'You need an innovation strategy', the 'Innovation Landscape Map' can be visualised within the following matrix:

The Innovation Landscape Map

When creating an innovation strategy, companies have a choice about how much to focus on technological innovation and how much to invest in business model innovation. This matrix, which considers how a potential innovation fits with a company's existing business model and technical capabilities, can assist with that decision.

	LEVERAGES **EXISTING** TECHNICAL COMPETENCES	REQUIRES **NEW** TECHNICAL COMPETENCES
REQUIRES **NEW** BUSINESS MODEL	**DISRUPTIVE** • **Open source software** FOR SOFTWARE COMPANIES • **Video on demand** FOR DVD RENTAL SERVICES • **Ride-sharing services** FOR TAXI AND LIMO COMPANIES	**ARCHITECTURAL** • **Personalized medicine** FOR PHARMACEUTICAL COMPANIES • **Digital imaging** FOR POLAROID AND KODAK • **Internet search** FOR NEWSPAPERS
LEVERAGES **EXISTING** BUSINESS MODEL	**ROUTINE** • **A next-generation 3 series** FOR BMW • **A new index fund** FOR VANGUARD • **A new 3-D animated film** FOR PIXAR	**RADICAL** • **Biotechnology** FOR PHARMACEUTICAL COMPANIES • **Jet engines** FOR AIRCRAFT MANUFACTURERS • **Fiber-optic cable** FOR TELECOMMUNICATIONS COMPANIES

Source: Corning: Gary P. Pisano, from "You Need an Innovation Strategy", June 2015

When creating an innovation strategy, companies have a choice in how much to focus on technological innovation and how much to invest in business model innovation.

In maritime, the data-driven condition-based maintenance business model is not a 'Routine' innovation. DCBM could be considered 'Disruptive' once the industry has developed all of the technical competency required to create and implement such processes. Over time, OEMs are expected to develop the required capabilities and technology to deliver this new business model, however 'digitising equipment' may not, by itself, be sufficient to deliver the minimum required economic value demanded by investors.

Where that economic value falls short in delivering the required ROI, we may find ourselves in a situation where new technology stakeholders need to enter the industry in order to generate the required returns. This would require an 'Architectural' level of innovation – the most challenging pathway for well-established industries, according to the model.

The maritime technology conundrum

In a 2017 article for the Harvard Business Review, Greg Satell categorises technological innovation according to two parameters – how well the domain is defined, and how well the problem is defined.

HOW WELL IS THE PROBLEM DEFINED?		HOW WELL IS THE DOMAIN DEFINED?: NOT WELL	HOW WELL IS THE DOMAIN DEFINED?: WELL
	WELL	**BREAKTHROUGH INNOVATION** Mavericks Skunk Works Open innovation/prizes	**SUSTAINING INNOVATION** Roadmapping R&D labs Design thinking Acquisitions
	NOT WELL	**BASIC RESEARCH** Research divisions Academic partnerships Journals and conferences	**DISRUPTIVE INNOVATION** VC model Innovation labs 15%/20% rule Lean launchpad

Source: Greg Satell

In the case of data-driven condition-based maintenance, the problem is considered well defined, although the opportunities that exist to solve the problem have not yet been fully defined; similarly, the domain is also well defined, although the domain within a future operating model could be different from today.

We believe the industry sits within the 'Sustaining innovation' quadrant at our current DCBM starting point, and will evolve towards the 'Breakthrough innovation' sector through our technology development pathway. From there, we should move towards fully data-driven decision-making business models for vessel equipment, before improving further to viewing the ship as a 'system of systems' and subsequently reaching the end goal of having the ship as an integral part of a wider value chain network.

Technology readiness is typically seen as a fundamental pilar in transforming operating business models – once the technology exists, we can create business cases that apply that technology to create new ways of working.

However, the technology required to support maritime maintenance decision making based purely on data does not yet exist on board ships at the required level of maturity. Where the technology does exist, it has been applied at a small fraction of the scope required to create significant operational efficiencies.

Solving the remaining challenges requires two further developments to occur – we must implement technology that addresses our requirements at the 'function' and 'system' level, and we must ensure that such technology demonstrates a level of accuracy and reliability capable of meeting the levels of performance and safety compliance required.

Resolving the first of these points and implementing technology that addresses our requirements is perhaps the most crucial in changing the way our industry performs maintenance, kickstarting the move towards a digital business model. It is the most important step, and yet also the most difficult to achieve, as it requires a re-balancing of levels of involvement by stakeholders and a move towards placing systems integrators centre stage in the management of operational performance aboard digital ships.

Call to Action

The maritime industry is in the midst of a major shift in operational processes that will challenge our ability to adapt to new global demands, with the twin drivers of decarbonisation and digitalisation creating disruption in legacy processes and forcing shipping to embrace new ways of working.

As such, it is an appropriate time to seize the opportunity to collaboratively transform maritime industry operations through the implementation of data-driven Condition-Based Maintenance (DCBM) processes for the benefit of all industry stakeholders.

For Classification Societies, these technologies can offer a pathway to new methods of risk assessment, allowing inspection regimes to become more intelligent and effective. For Ship Owners, the shift to data-driven processes offers an opportunity to achieve significant ROI by investing in new methods of maintenance management that can reduce operational downtime and maximise the value of fleet assets.

Original Equipment Manufacturers (OEMs) have the opportunity to elevate their product offerings and become an integrated industry partner by delivering data-driven value-added services. For the insurance and finance industries, these changes will help to provide increased levels of confidence in assessments of vessel condition, lowering coverage risks. Cargo Owners can also benefit from increased predictability in supply chain timelines and scheduling due to the predictive improvements that can be delivered by DCBM.

The authors encourage all industry stakeholders to explore the possibilities of these technologies and take their first steps on this journey, so that together we can embrace a data-driven future to create a range of improvements beyond just enhancing safety – securing competitive advantage, reducing overheads, and delivering excellence in maritime operations.

Annexes

Annex 1

Technologies and tools to support the development of data-driven algorithms and machine learning models

- **Generalised machine learning algorithms designed to operate across multiple use cases**
  Introducing Pathways: A next-generation AI architecture (blog.google)

- **Paid-for and open-source data-driven algorithms and source code libraries**
  Amazon SageMaker JumpStart – Amazon Web Services
  GitHub – The NASA Prognostic Python Packages
  Machine Learning – Google AI

- **ISO/IEC standards for AI and Machine Learning**
  ISO/IEC TR 24030:2021 Information technology — Artificial intelligence (AI) — Use cases
  ISO/IEC 23053:2022 Framework for Artificial Intelligence (AI) Systems Using Machine Learning (ML)
  ISO/IEC 24668:2022 Information technology — Artificial intelligence — Process management framework for big data analytics

- **Examples of ML Ops Frameworks**
  ML Ops: Machine Learning Operations (ml-ops.org)
  Microsoft Azure
  Machine Learning with MATLAB – MATLAB & Simulink (mathworks.com)

- **Examples of ML DevOps Frameworks**
  Ansys Twin Builder | Create and Deploy Digital Twin Models
  What is Digital Twin Software | Digital Twin Solutions | AVEVA
  Predictive Maintenance Toolbox – MATLAB (mathworks.com)

- **Industrial AI marketplaces**
  ABB Ability. Industrial Internet of Things (global.abb)
  KI-Marktplatz
  Siemens Xcelerator

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