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Maintenance routine simulation with data-driven approaches applied to naval and shipping sectors

by

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Abstract

Condition Based Maintenance (CBM) has been successfully adopted in decades by many types of industry, however the naval and shipping sectors have shown low acceptability, mainly because lack of or little evidence of value for money (Shorten, 2013; Informa Engage, 2020). Although there is extensive literature about CBM and much research has been expended on smart technologies and digitalization in the last decade, the implementation of data-driven maintenance techniques still presents some challenges to be overcome. This work explores these challenges and propose a systematic management plan for smart modelling and simulation of maintenance routine of naval and shipping sectors.

Keywords: Ship maintenance, data-driven maintenance, Discrete Event Simulation, workforce demand smoothing, maintenance scheduling, Condition Based Maintenance.

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Statement of originality

I declare that the work in this dissertation was carried out in accordance with the requirements of Brunel University's Regulations and Code of Practice for Taught Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, this work is my own work and work done in collaboration with, or with the assistance of others, is indicated as such. I have identified all material in this dissertation which is not my own work through appropriate referencing and acknowledgement. Where I have quoted or otherwise incorporated material which is the work of others, I have included the source in the references. Any views expressed in this dissertation, other than referenced material, are those of the author.

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Glossary

AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
CBM	Condition Based Maintenance
CBM^+	Condition Based Maintenance concept developed by the USA Department of Defence
CBR	Case-Based Reasoning
CDMA	Code-division multiple access
CGAN	Conditional Generative Adversarial Network
CLIT	Clean, Lubricate, Inspection and Tightening
CM	Corrective Maintenance
CSEM	Crew Size Evaluation Model
D2B™	Device-to-Business
DAIF	Data Assessment Imputation Framework
DES	Discrete Event Simulation
DGRU	Deep Gated Recurrent Unit
DoD	United States of America Department of Defence
DSS	Decision Support System
EAMS	Enterprise Asset Management System
EIS	Engineering Immune Systems
ETTF	Estimated Time To Failure
EVDO	Evolution-Data Optimized
EWMA	Exponentially Weighted Moving Average
FDILA	Flexible Data Input Architecture
FMEA	Failure Mode and Effects Analysis
FMECA	Failure Modes, Effects, and Criticality Analysis
GA	Genetic Algorithm
GPRS	General Packet Radio Services
IACS	International Association of Classification Societies
IAS	Integrated Automation System
IEEE	Institute of Electronics and Electrical Engineers
IMO	International Maritime Organization
IMS	Intelligent Maintenance System
ISO	International Organization for Standardization
KPI	Key Performance Indicator
KRR	Kernel Ridge Regression
MAR	Missing at Random
MCAR	Missing Completely at Random
MCM	Mass Customised Maintenance
MEMS	Micro-Electro-Mechanical Sensors
MNAR	Missing Not at Random
MTBF	Mean Time Between Failures
OEM	Original Equipment Manufacturers

PBL	Performance Based Logistics
PCA	Principal Component Analysis
PdM	Predictive Maintenance
PHM	Prognostics and Health Management
PLC	Programmable Logic Controller
PM	Predetermined Maintenance
PMS	Planned Maintenance System
PvM	Preventive Maintenance
R3M	Real-time Model Matching Mechanism
RBM	Risk-Based Maintenance
RCM	Reliability Centred Maintenance
RNN	Recurrent Neural Networks
RUL	Remaining Useful Life
SAE	Society of Automotive Engineers
SCADA	Supervisory Control and Data Acquisition
SOLAS	International Convention for the Safety of Life at Sea
TD-SCDMA	Time-division Synchronous Code-division Multiple Access
TPM	Total Productive Maintenance
WCDMA	Wideband Code Division Multiple Access

See table 1 for maintenance attribute symbols.

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1 Introduction

1.1 Background

Maintenance techniques evoluted from Corrective Maintenance (CM) to Preventive Maintenance (PvM). The philosophy of CM is to make interventions on the systems when they have failed, while PvM intents to undertake maintenance activities before the failures occur. PvM was further divided into Predetermined Maintenance (PM) and Condition Based Maintenance (CBM) categories. The first foresees maintenance activities scheduled in intervals based on the expected life of components, and the second includes combination of inspections, monitoring and analysis of the actual equipment condition which allow the decision making about the maintenance actions (Jimenez, Bouhmala and Gausdal, 2020). The improvement for CBM was the Predictive Maintenance (PdM), which seeks to forecast the maintenance tasks based on the analysis of condition trends. These trends are built from historical data and can be assessed in real-time if there is communication between the sources (files, databases, sensors (Fadzil, 2020)) and the analytical system, or in offline mode, when the historical data from sources is logged and periodically analysed afterwards.

Although CBM emerged on 1940s in a railway company, then on 1970s, the automotive, aerospace, military, and manufacturing industries were already experiencing benefits in both efficiencies and cost (Prajapati, Bechtel and Ganesan, 2012), the shipping sector still presented low adoption of this technique in 2010s, with only 2% of the world classed ships running with CBM (Shorten, 2013). This scenario seemed to be improving in the following decade, according to the survey carried out in 2020 by Informa Engage on behalf of Inmarsat (Informa Engage, 2020). It shown that on average 23% of respondents were testing or deploying digital applications related to fleet and vessel performance, which 61% of these respondents had been fully or commercially deploying to engine performance monitoring and analysis, and 49% of the same respondents adopted to other equipment condition monitoring and analysis. Furthermore, it had presented that 17% of respondents intent to deploy digital applications to fleet and vessel performance in near future.

Considering CBM a technique developed more than 80 years ago and adopted with success by many engineering sectors (Kobbacy and Murthy, 2008, p. 115), it is surprising that 77.9% of interviewed maritime companies are not using it, and only 17% intend to adopt some sort of condition monitoring technique. Moreover, only about half of the companies which adopt CBM applies to equipment other than engines, which evidence that there is room for integration of other relevant systems of ships. Furthermore, designing reliable systems and adopting affordable monitoring techniques are the stepstone of future unmanned/autonomous ships (Brocken, 2016).

The (Informa Engage, 2020) also pointed the concerns that challenge ship owner/managers to implement digital solutions on ships. The most quoted challenge (22%) was the lack of or little evidence of value for money. Regarding expecting savings in operation costs, 58% of respondents expected lower than 10% savings due to adoption of digital applications, which means that the investment to adopt CBM cannot be high to guarantee satisfactory economical return. Other challenges highlighted up to the third rank of answers were risk of cyber-attack, lack of staff training on vessel and ashore, lack of data standardisation, disjointed data and systems, management´s lack of awareness, hardware cost and installation time, bandwidth availability and cost, and inability to analyse and make use of the data in real time. Some of the challenges identified by the survey have been addressed in the academic literature, but joining the solutions altogether is a work to be done.

The options to implement CBM and smart technologies are vast, and the required degree of digitalization is not obvious. Looking back to Informa Engage (2020) survey, 40% of respondents tend to seek smaller innovative companies and 36% tend to co-create digital solutions with early stage or scale-up companies. According to (Clayton, 2021), “It’s also important for digitalisation to deliver real savings to ship owners and operators. For that to happen, companies need to understand what is useful and what is not (…) The general consensus was that progressive owners are embracing digitalisation but the majority are content to wait.”

Considering the expected lifespan of general merchant ships as 25 years (Dinu and Ilie, 2015) and the respective average age, in 2020, of bulk carriers, oil tankers and container ships (which correspond as 85% of total world dead-weight cargo capacity) as 10.2, 19.1 and 12.7 years old (UNCTAD, 2020), it can be inferred that many ships will operate in the following decades without CBM technologies unless the shipowners get convinced of the value for money of such techniques.

Although there is extensive literature about CBM and much research has been expended on smart technologies and digitalization in the last decade, the implementation of data-driven maintenance techniques still presents some challenges to be overcome. This work explores these challenges and the solutions found in academic literature and propose a systematic management plan for maintenance routine of naval and merchant systems. This management plan was exemplified using a maintenance dataset from a Brazilian navigation company, which was kept anonymous to comply with confidentiality requirements.

1.2 Aims and objectives

Bringing forward the Brazilian company's case to the state-of-art developments, this work aims to identify the challenges and propose a methodology for smart data acquisition for a modern simulation and modelling of maintenance routine applied to naval and shipping sectors.

The first objective is to identify technical solutions to overcome the challenges to adopt CBM methodologies, which includes some applied to other industries that can be adapted to naval and shipping sectors. This goal will be reached by reviewing the current literature that aims to provide solutions for the challenges of implementing maintenance routine management with data-driven approaches.

The second objective is to propose a methodology for managing smart data acquisition considering a significant level of information which do not overstate or unnecessarily burden installation cost and system complexity. The proposed framework includes modelling and simulation of maintenance routine of ships considering real-time approach or periodic historical based analysis. The Brazilian company's case will demonstrate its applicability.

The design of the maintenance system infrastructure will be not part of the scope of this work since the main concern is to apply the maintenance data to a management plan.

Since all these techniques start from the data acquisition, this work presents a proposal of a systematic selection of maintenance attributes required for a management model of data-driven maintenance system.

1.3 Methodology and dissertation structure

Initially, the challenges for implementation of a data-driven maintenance system will be identified and detailed through literature review, followed by an analysis to organise and compare different existing approaches that can be applied. This task will help to identify the data-driven maintenance approaches that can be applied to the naval and shipping sectors, as stated for the first objective of the work, and will be developed in the literature review, chapter 2. A summary of the challenges and solutions are presented in the Appendix.

The second part is to develop a management plan to make the acquired data available to be applied to modern maintenance systems, considering a systematic selection of approaches according to the findings of the first task. The Brazilian company case will illustrate the proposed management plan. This task will be developed in the chapter 3, and its results and discussion in the following chapters, respectively.

2 Literature review

The organization of the literature review aims to expose the technical/academic solutions for the challenges of implementing data-driven maintenance and decision support systems. Each challenge is followed by works that explored some solutions. A summary of the challenges and solutions are presented in the Appendix.

2.1 Challenges for implementation of data-driven maintenance techniques

Lack of or little evidence of value for money and management´s lack of awareness.

(Psarommatis *et al.*, 2022) purposed a model to provide a tool aiming to assist production managers to understand five generic key performance indicators (KPIs) which were translated into a continuous real-time cost function. The translation of engineering data of physical systems and operations into a common financial language make clear and easier to company departments seek their priorities and identify profitable decisions. Although the model was validated only in a batch order-based manufacturing environment, the concepts can be exported to ship industry to overcome the challenge of giving evidence to value for money and better understanding and awarening managerial issues in a real-time engineering system.

Lack of data standardisation, disjointed data and systems and lack of staff training on vessel and ashore.

The work of (Ford, McMahon and Rowley, 2013) described the challenge of the Royal Navy to exploit vast quantities of information regarding maintenance of complex fleet of warships and submarines. The authors cite (Kane and Alavi, 2007) definition of “exploitation” as “incremental learning focused on diffusion, refinement, and reuse of existing knowledge”, and highlighted the attention that should be taken about the information regarding to fuzziness (lack of detail), incompleteness (what is unknown or left out), and randomness (lack of pattern). The work concluded that in-service phase, which includes operation and maintenance and most cost of ownership of assets, presents stakeholder information exploited by “Suitable Qualified and Experienced Personnel”, which is a limited and expensive resource, and identify key data elements to better exploit information about marine surface ship domain.

(Michala, Lazakis and Dikis, 2016) worked with the accident/incident record keeping system of a shipping company and proposed a method for evaluating the existing data and combining to the Planned Maintenance System (PMS). The first review of the record system found problems such as duplication of information, manual handing of the data, lack of automation and disjoined systems between company departments. After automating and integrating of the record keeping system with the PMS and records of Safety and Environment departments, they proposed the introduction of a CBM system.

(Cullum *et al.,* 2018) revised the Reliability Centred Maintenance (RCM) framework of a naval fleet, which were conducted together with PM and CBM. The authors identified that the condition-based and PM actions were scheduled at non-uniform intervals due to the assessment of the condition of the equipment in a non-favourable approach from a managerial perspective. Other factors such as lack of appropriate training, human error and subjectivities introduce some uncertainty into maintenance scheduling, which decisions were conducted manually by personnel. They suggested a Risk-Based Maintenance (RBM) to deal with the limitations of PM and RCM and schedule maintenance dynamically using risk assessment as a trigger.

The work of (Koons-Stapf, January, 2015) provided a guidance to implement CBM^+, which is a concept developed by the USA Department of Defence (DoD) that embraces all the maintenance structure of a system's life-cycle. She broke down CBM+ activities into CBM tools, such as RCM and Failure Modes, Effects, and Criticality Analysis (FMECA), CBM enablers, such as sensors and information tools, and CBM ancillary enablers like redesigning systems to allow monitoring of all failure modes. She also identified elements of business/management and technical categories. Among the first, there are the DoD polices and doctrines to establish process, procedures, technological capabilities, information systems and logistics concepts; the business strategy to increase effectiveness and efficiency by avoiding unnecessary maintenance activities; and the relationships between RCM analysis and failure management strategies. The technical elements are the infrastructure of hardware and software; the architecture for CBM^+ that may cross the functional, organizational and physical boundaries; and the data strategy, which should be based on open systems that follow commercial standards established by institutions such as the International Organization for Standardization (ISO), Institute of Electronics and Electrical Engineers (IEEE), Society of Automotive Engineers (SAE) etc. The data strategy also determines the level of predictive activities and health assessments of systems. A business case should support and validate these aspects of CBM^+ implementation, which can be gradually applied to life-cycle activities of a system. Although this model for CBM implementation was developed for the USA military forces, it is easily adaptable to commercial organizations. However, she also highlighted that Performance Based Logistics (PBL) contracts with DoD sometimes do not contemplate CBM strategies due to high investment and the long-term required for perceiving cost savings.

Hardware cost and installation time

(Michala and Lazakis, 2016) defended that the adoption of CBM in ships is mostly inhibited by the cost of installation, the capital investment in training staff, the lack of trust in the prediction capabilities of the technology and the security of data. Therefore, they presented a novel method to reduce installation costs based on wireless data transmission, which makes easier the installation and lower the time to setup, and a novel decision support system (DSS) solution to be used onboard a ship with minimal initial training.

Bandwidth availability and cost

(J. Zhao *et al.*, 2013) provided an alternative to the still expensive and limited bandwidth satellite communication (Informa Engage, 2020) by applying communication technology such as 3G (WCDMA/CDMA EVDO/TD-SCDMA) and GPRS with lower cost, higher bandwidth, and satisfied coverage for ships on inland waterways. They standardized the data across a fleet of hundreds of tenders and developed a fleet management centre system in a web application. Therefore, operating parameters and alarms were snapshot periodically, coded, packaged, and uploaded to shore fleet technical management centre when connection was available. To conduct the CBM of a ship, the information was replicated both onboard of each ship and onshore.

Inability to analyse and make use of the data in real time

(Fadzil, 2020) developed a novel architecture that accounts for known and unknown parameters, such as environmental conditions like humidity, into machine learning algorithm and prediction of state, and linked to embedded systems, with capacity to self-organize the parameters in order of its importance in real-time, providing system status based on KPIs. The proposed architecture provides adaptive strategies to optimise the performance of systems in real-time.

2.2 Data-driven maintenance approaches

Choosing data-driven maintenance approaches

According to (Liao and Köttig, 2016) the methods to estimate the remaining useful life (RUL) of a system are data-driven, model-based or a combination of them. The first method relies on previous or observed data to make predictions, which are generally calculated by statistical methods, reliability functions and/or artificial intelligence methods. Model-based method attempts to describe the failure mechanisms by mathematical descriptions of the degradation process, which is often evaluated as case-based (Behera and Misra, 2021). Considering Prognostics and Health Management (PHM) systems as integration and augmentation of CBM and RCM, (Ellefsen *et al.*, 2019) represented the diagnostics and prognostics approaches as shown in figure 1.

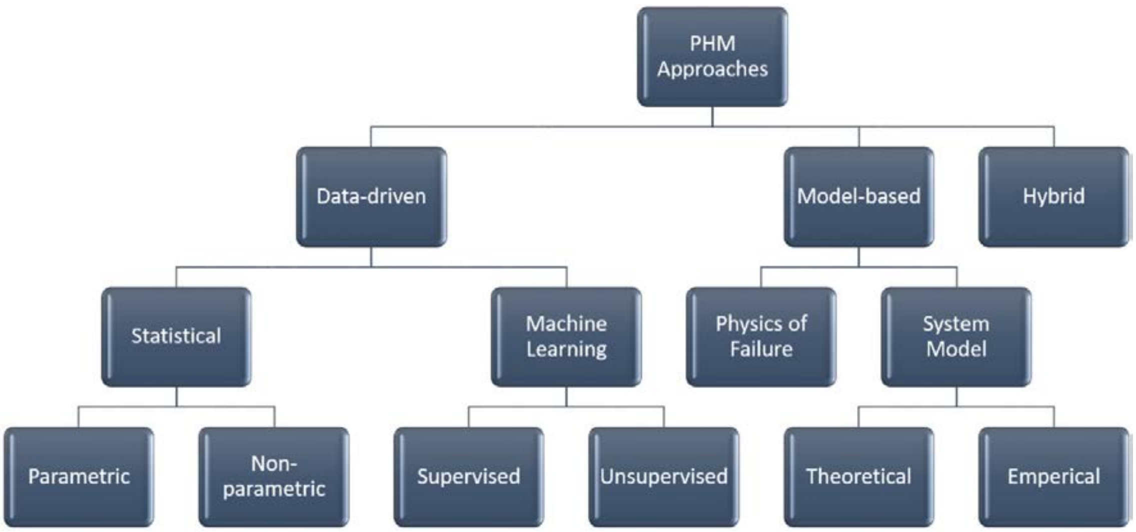

Figure 1. Diagnostics and prognostics approaches (Ellefsen *et al.,* 2019).

(Liao and Köttig, 2016) grouped the hybrids approach as:

- "Use a data-driven method to infer a measurement model and a model-based method to predict RUL.
- Use a data-driven method to replace a system model in a model-based RUL prediction method.
- Use a data-driven method to predict future measurements which are used within a model-based method.
- Combine a data-driven method and a model-based method for prediction by "averaging" their results."

Due to modern enablers such as sensors, instruments, servers and connected systems in a big data, there is a shift towards data-driven (Ellefsen *et al.*, 2019; Fadzil, 2020; Behera and Misra, 2021) and hybrids approaches that uses data-driven methods to predict future conditions to be used in a model-based maintenance system (Liao and Köttig, 2016). Hybrid approaches that fuses sensor-based data and model-based information may be more complex to design and implement but they often take advantages over a single model approach (Hansen, Hall and Kurtz, 1995; Kristensen, 2021).

Defining input parameters

Considering that the purpose of maintenance is to avoid breakdowns by scheduled or unscheduled downtimes, (Roosefert Mohan *et al.*, 2021) classified the five sources of breakdowns as "poor usage condition, poor basic condition, deterioration, operating error and designing error", where condition refers to the basic operation without any functional failure, deterioration and defect. They grouped the countermeasures for breakdowns as reactive, the actions taken after happening breakdowns, and proactive, which englobe a variety of actions and programmes such as Clean, Lubricate, Inspection and Tightening (CLIT), PM checklists, CBM, Kaikaku Hozen (HZ), Kaizen, Total Productive Maintenance (TPM), and many other selected according to the company's maintenance strategy. All these approaches rely on exhaustive lists/steps of maintenance actions, expert evaluations or both, as well as all the modern data-driven approaches developed recently.

The work of (Jimenez, Bouhmala and Gausdal, 2020) focused on developing a predictive maintenance solution based on real-time monitoring and artificial intelligence for the maritime industry. They collected data from main engines and compressors and analysed their correlation with software R®. The data came from lube oil laboratory reports, vibration analysis and performance data taken from 537 relevant parameters selected by experts among many others monitored by the Integrated Automation System (IAS) of the ship. The work shown practical challenges of data acquisition and processing such as the delay in obtaining the results of lube oil analysis, which often strikes CBM implementations in maritime sector. Therefore, oil contamination sensors such as used by (Roosefert Mohan *et al.*, 2021) could provide real-time data of lube systems. Other challenge was the historic characterization of failure data since two situations occurred: there were few failures during the data acquisition process, and failures were prevented by crew action such as unreported maintenance or changes in operational profile without any maintenance action taken. The lack of failure data pattern would make predictive algorithms based on machine learning techniques ineffective. Besides, not knowing the respective maintenance action to be taken would make any maintenance scheduling systems incomplete. The work succeeded in verify the correlation between all the performance data and showing that it is possible to automatically identify the most important parameters that drive others, which can be useful for implementation of artificial intelligence algorithms.

Reducing the dependence of experts

Many data-driven approaches focus on reducing or eliminating the dependence on the experts and replacing their involvement by prognostics and predictions algorithms. In the naval sector, this objective is associated with the need for reduction of human errors, which accounts for 75% to 96% of maritime accident causes (Levande, 2017), and the actions required for implementing autoships (semiautonomous ships) (Ellefsen *et al.*, 2019) or autonomous ships.

Before de advent of Industry 4.0 terminology, (Han and Yang, 2006) called as e-maintenance the system able to use the Internet to connect a maintenance centre to the local maintenance. Their proposed framework for the local maintenance (at the manufacturer venue) including a real-time condition monitoring system; fault diagnosis and degradation prediction modules; and database storage and presentation regarding maintenance strategy. Before sending raw data acquired by sensors and micro-electro-mechanical sensors (MEMS) to the condition monitoring and diagnosis systems, it was applied pre-processing approaches such as high, low and band filtering, integration, wavelet transformation, average etc, into their appropriated domains (time, frequency, cepstrum, wavelet etc), to reduce the required storage space in the database. Only relevant features should be transferred to increase processing efficiency. For an electric motor, their example were vibration, current and electromagnetic field signatures, acoustic noise and chemical analysis, infrared, temperature and partial discharge measurements. The condition monitoring module compared the data trends to the operational limits and alerts in case of abnormal condition was already happening. The authors warned about the difference of setting operational limits in running condition, which might divert from industrial standards and depend on expert opinions. The faulty diagnosis module is supported by a laboratory which perform the measurements, tests or analysis on the equipment. The initial fault diagnosis data is taken form expert opinions and augmented with artificial fault diagnosis data presented in specialized literature. The data structure is then automated by feeding an artificial intelligence (AI) technique with the results of the principal component analysis (PCA) of the relevant sensor data in the respective domain. The AI reduces the dependence of the expert opinion and improves accuracy of fault diagnosis by applying techniques such as expert system, artificial neural network (ANN), fuzzy logic system, and genetic algorithm (GA). The method applied by the authors was training an ANN to learn data patterns from selected features and optimized parameters by a GA system. This task was structured as case-based reasoning (CBR) system, which intends to provide solutions for a new problem by adapting solutions from old problems. The CBR substitute the initial fault diagnosis data and eliminate redundant cases by creating and combining existing ones according to similar degree of closeness. The authors summarized the process into four main steps: case collection, case normalization, case feature extraction and training the ANN system. The last step may still depend on expert opinion to solve ambiguities rose from few solutions that match the current problem and to attribute/revise the degree of importance of occurrence symptoms, component, fault cause, corrective action etc, according to data analysed in the CBR. Finally, the structure of maintenance centre and the local maintenance allows to reduce manpower and experts in the local maintenance, although the local experts are still needed to evaluate the solutions and to set the local maintenance strategy. Furthermore, near-zero downtime operation can be achieved by implementing an information flow with right communication sequence between maintenance centre and the local maintenance.

Lack of continuity or incompleteness of acquired data

Other challenge that arises from digital data acquisition is the lack of continuity or incompleteness of data, which can be caused by faulty sensors or communication problems. According to (Cheliotis *et al.*, 2019), a time series collected from maritime machinery systems may have 4.4% to 26% of missing values. They are basically divided into three types. The first is Missing Completely at Random (MCAR), which the missingness is independent of the data. The second is Missing at Random (MAR), which the missingness depends on another feature. The third is Missing Not at Random (MNAR), which the missingness is due to the feature itself. Missing data can also include data intentionally removed from the sample such as outliers or transients. The evaluation of missing data takes place in the pre-processing step that follows acquisition of raw sensor data. According to (Ellefsen *et al.*, 2019) this step includes cleaning and data analysis. Cleaning tries to eliminate human and sensor faults and includes methods such as amplification, data compression, data validation, denoising and filtering, while data analysis extracts the representative regime to be considered in the failures and faults detection. The work of (Velasco-Gallego and Lazakis, 2020) approached the problem of missing data in a real-time CBM of a main engine of a merchant ship. They compared 20 widely implemented methods of imputing incomplete values in real-time machine learning and time series forecasting algorithms. Before testing the methods, the raw data was filtered to eliminate transient and manoeuvring regimes and only steady operational states of the machinery was evaluated against the Original Equipment Manufacturers (OEM) thresholds. The pre-processing step included data standardization to ensure that all features are equalized. The work concluded that the Autoregressive Integrated Moving Average (ARIMA) was the best univariate imputation technique for stationary data. In the work (Velasco-Gallego and Lazakis, 2021b), the same authors suggested a hybrid model of the first-order Markov chain for univariate imputation in tandem with a multivariate imputation approach based on a comparative methodology of 16 machine learning and time series forecasting models. Then in the work (Velasco-Gallego and Lazakis, 2021a) they proposed a Data Assessment Imputation Framework (DAIF) to verify the accuracy of any imputation method. In this work they denoised the machinery data using Exponentially Weighted Moving Average (EWMA) technique and concluded that for MAR data the Kernel Ridge Regression (KRR) leads to better results for large gaps, while for MCAR context GA-ARIMA, which is an association of a Genetic

Algorithm to determine the coefficients of ARIMA, had better results. MNAR was not tested.

Unavailability of fault-data

(Behera and Misra, 2021) approached the problem of fault-data unavailability that rises from complex systems with multi-variate sensor data and causes imbalanced training dataset to be overcome by the fault-prediction algorithms. The Prognostics and Health Management (PHM), represented by the estimation of remaining useful life (RUL), was analysed by a conditional generative adversarial network (CGAN) and a deep gated recurrent unit (DGRU) neural network approaches. The generative adversarial network (GAN) has the ability to create realistic artificial data of fault diagnosis to balance the missing data in the acquired sample. The CGAN is an improved architecture of GAN that has the advantage of providing better convergence to unstable and vanishing gradient problems during model training. It uses conditional labels and allows to learn reasonable mappings with limited training data. The DGRU is a variation of the recurrent neural networks (RNN) which allows for self-feedback neurons to obtain information from data processed in previous time steps and to integrate them into the sequential monitoring data. DGRU works better with long-term dependencies between cell states than RNN. It performs the RUL prediction using the augmented data generated by CGAN. The authors tested this technique in a turbofan engine and achieved accurate real-time predictions with smaller latency, lower parameters, and lower required memory than other similar over-sampling approaches that deals with imbalanced data.

Simulating physical world using real-time-data

Alternatively to the examples of data-driven methods above, a hybrid solution was proposed by (Tavakoli, Mousavi and Komashie, 2008), which was a generic framework that uses real-time-data-driven techniques to feed a simulated model of a physical world problem. The architecture is composed of a Data Integration and Processing and a Simulation Modeling Engine. The first provides flexible acquisition of any type of input data by using a multi-layer structure called Flexible Data Input Architecture (FDILA), which is responsible for real-time data acquisition, data fusion, and pre-processing, including filtering and curve fitting. The second uses Discrete Event Simulation (DES) method to simulate the physical environment in a model that reacts to real-time events with aid of a Real-time Model Matching Mechanism (R3M). This correspondence between physical and cyber-physical model is also named as Digital Twin (Agalianos *et al.,* 2020; Sakr *et al.,* 2021). The authors defend that DES in real-time control present some advantages over traditional simulation, such as not heavily depending on historical data, which the mining process and analysis is always time consuming; not suffering from data obsolescence, which may affect the reliability of predictions; and cheaper, since the time to build and run the simulation models are lower. The framework also allows to stop the stream of real-time data into the model and feed it with modified input data to simulate "what if" scenarios. Other works of (Jeon and Kim, 2016; and Mousavi and Siervo, 2017) demonstrated that DES can better capture real-world complexities regarding system performance, system monitoring, prediction and scheduling, which can also be associated with artificial intelligence techniques (Danishvar *et al.,* 2021).

2.3 Decision support systems

Implementing CBM to old assets

For the sake of implementing digital maintenance, the rail transportation sector has some similar difficulties of the naval sector. According to (Hodor, 2018), many assets are 20 to 30 years old and lack the required sensors and capabilities to run CBM. Retrofits and upgrades in this sense are sometimes almost impossible. There are shore fixed systems, but communication challenges to transfer online data also impact rolling assets, especially underground or in the countryside, where telecommunication companies have poor network. Therefore, the author warned the importance of clarifying what to monitor, including certifying what are normal and abnormal conditions, to truly contribute to on-going maintenance strategy. He also criticised initiatives based only on historic data of past failures. This data is useful for predictions and to train machine learning techniques only if combined with observed CBM data. He defends the use of supervised (that follows labelled rules) or unsupervised (that identifies structure relationships) machine learning techniques over artificial intelligence or deep learning since the ability of the former to learn without being explicitly programmed. The author added other caveats to implement CBM, such as: lack of suitability of some systems to provide enough available data to make predictions; indiscriminate collection of data before properly defining the problem to be solved, wasting time and money; confusing factors such as under fitting and

Simpson's paradox that mislead the predictions; judgements based only on predictions and not together with company's insights regarding to the following actions after a failure prediction. The author considers the digital maintenance as the visible part of the iceberg, while the largest immerged one concerns about the enterprise asset management system (EAMS) that consolidate and integrate all information into a single system able to help operators to prioritize and plan maintenance. Regarding the management of volume and variety of data, the author also prefers data lake ecosystems over warehouse types of big data, because data lakes are open source, do not need structured data, and are mostly applied to predictions and prescriptions of internal and external sources of data.

Techniques for modelling maintenance management systems

Considering that hybrids approaches using data-driven and model-base methods potentially produce superior results than a single one (Kristensen, 2021; Hansen, Hall and Kurtz, 1995), the works regarding model-based support systems are often based on simulation frameworks that are able to gather all company's requirements (Alrabghi, Abdullah and Tiwari, 2016). One technique largely used is DES, since it has the capacity of modelling the physical system and reproducing the chain of events ruled by maintenances attributes and company's constraints. DES models can be built into a single software, and it has been applied to maintenance decision support models of many industrial sectors, such as:

Manufacturing: (Sakr *et al.*, 2021; Psarommatis *et al.*, 2022; Wakiru *et al.*, 2020; Golbasi and Turan, 2020; Abbasli and Mammadli, 2020; Mousavi and Siervo, 2017; Alrabghi, Abdullah and Tiwari, 2016; Alrabghi, Abdullah and Tiwari, 2015; Lu and Olofsson, 2014; Oyarbide-Zubillaga, Goti and Sanchez, 2008; Han and Yang, 2006)

General maintenance: (Benker, Rommel and Zaeh, 2022; Akl *et al.*, 2022; Budiono, Siswanto and Kurniati, 2021; Urbani, Brunelli and Collan, 2020; Alrabghi, A. *. and Tiwari, 2016; Alabdulkarim, Ball and Tiwari, Dec 2011)

Civil aviation: (Meissner, Rahn and Wicke, 2021; Pohya *et al.*, 2021; Albakkoush, Pagone and Salonitis, 2021; Wang, Cui and Shi, 2017; Van den Bergh *et al.*, 2013; Dupuy, Wesely and Jenkins, Apr 2011; Bazargan and McGrath, 2003)

Military aviation: (Colbacchini *et al.*, Apr 2016; Bell and Teague, Apr 2014; Iwata and Mavris, 2013; Kang *et al.*, 2010; Mattila, Virtanen and Raivio, 2008; Salman *et al.*, 2007; Warrington, Jones and Davis, 2002)

Civil engineering: (Nili, Taghaddos and Zahraie, 2021; Devulapalli, Martinez and de la Garza, 2002)
Naval ships: (Lafond *et al.*, 2021; Schütze and Hughes, 2012)
Information technology and Telecommunication: (Lyubchenko *et al.*, 2020; Jiang *et al.*, 2016)
Offshore wind farms: (Ait-Alla *et al.*, 2020; Byon *et al.*, 2011)
Logistics: (Agalianos *et al.*, 2020)
Rail transporting: (Agostino *et al.*, 2020)
Automotive: (Zhang *et al.*, 2017)
Autonomous vehicles: (Dietrich, Krug and Zimmermann, Oct 2017)

Dealing with geospatial constrains

Maintenance in ships is a complex and chaotic activity (Lafond *et al.*, 2021). Apart from the challenge of scheduling resources and material, ship managers should consider some attributes of maintenance activities such as priority, precedence relationship, resources required, time required, working area required, proximity impacts, path impacts (Bertrand, 2020). In this sense, (Lafond *et al.*, 2021) considered geospatial constrains due to work area capacity, which refers to jobs or workers that can be co-allocated, proximity constraints, related to works in one area that affects adjacent areas due to logistic or safety reasons, and path constraints, related to work that makes a passage unavailable. To deal with the geospatial constraints the authors proposed a three-dimensional model presented as boxes which represent the compartments of the ship, and a colour map that shows the constraint status, see figure 2. Although the method adopted by the authors was model-based AI, heuristic methods and DES to schedule project tasks, they did not make it clear how DES was applied.

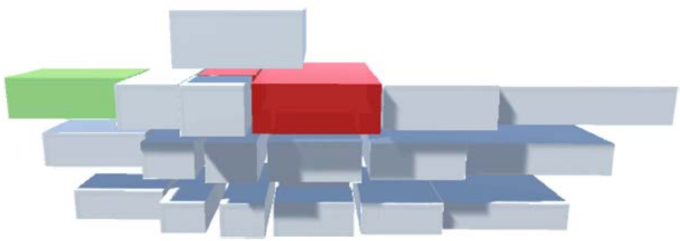

Figure 2. Geospatial constraint 3D model with a proximity conflict of tasks in red (Lafond *et al.,* 2021).

Defining required workload

28. The work of (Schütze and Hughes, 2012) applied DES to explore the cost savings that could be achieved by smoothing workload necessary to perform maintenance of warships Their model focus on dealing with timescales in delivering contracts with the Australian Department of Defence. They demonstrated the impact of opportunistic maintenances and urgent defects in the workload necessity, considering the scenarios of extra work allowed and delaying the maintenance period with overtime. (Lee, John D., 1997) proposed a Crew Size Evaluation Model (CSEM) based on DES to validate predictions for shipboard crew requirements. He collected data from shipboard observations, structured interviews, analysis of planned maintenance logs and logbook data.

Future maintenance management systems

An intelligent maintenance system (IMS), composed by two commercial applications, Watchdog Agent^{TM} and Device-to-Business (D2B^{TM}) platform, was proposed by (Huang *et al.,* 2005). The first is designed to acquire sensor data and make diagnostic and predictions of equipment faults. This intelligent agent is installed together with the programmable logic controller (PLC) in other to send processed data to the following agent instead of flooding the network with raw data, which might struggle with bandwidth limits. It alerts if there is an immediate maintenance needed, a maintenance due to cycle time, and long-term maintenance forecasting. The D2B^{TM} receives data from Watchdog Agent^{TM} and synchronizes the maintenance needs to the associated e-business that will provide spare parts and/or technical assistance. This system enables frameworks of mass customised maintenance (MCM) where maintenance companies can offer customized services to their customers, who can work with near-zero inventory. (Lee, J., Ghaffari and Elmeligy, 2011) foresee that systems like Watchdog Agent^{TM} will integrate an in-situ prognostics module of products and machines that will feed PHM systems able to manage their overall health state. They pointed PHM as the systems responsible for monitoring and predicting the progression of a fault and autonomously, or with some human aid, triggering maintenance schedule and asset management decisions or actions. The aim of this system is to optimize maintenance schedule, eliminate the unnecessary and costly preventive maintenance, and reduce costs by optimizing resources allocation and reducing lead-time for spare parts. The authors believe that PHM is a stepstone for achieving resilient, self-maintenance and Engineering Immune Systems (EIS). Resilient system is an evolution of PHM for complex environments that would be unpredictable to PHM, which *robust design* would deal with dynamic changes. Self-maintenance refers to a new design and system methodology that are able to monitor and diagnose itself and still maintain its functions if a failure or degradation happen, then making immediate repairs by using stocked spare parts. EIS is also a fault-tolerant system, which is inspired by the biological immune system, that predicts the system performance based on the predictions of faut tolerances or accommodations, and trigger maintenance schedule if a catastrophic failure would happen.

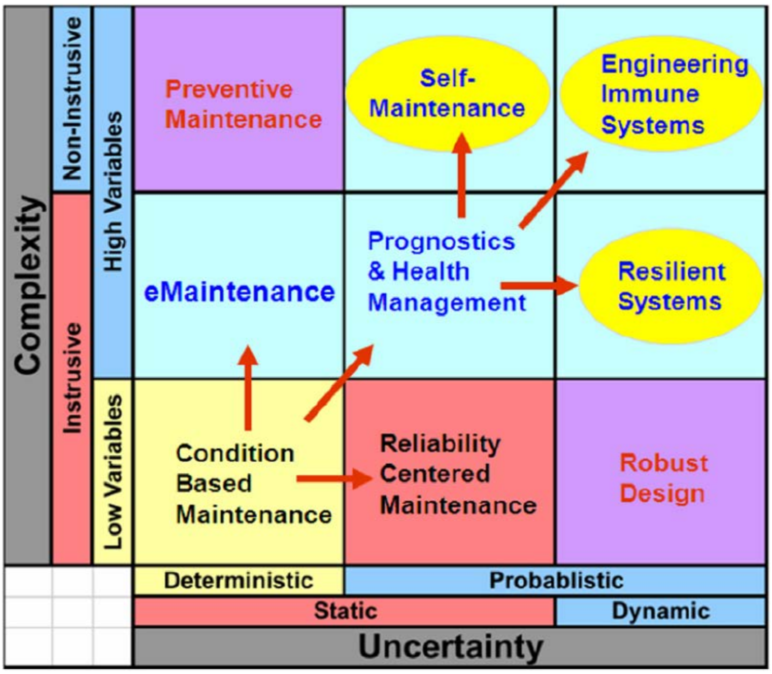

Figure 3. Maintenance systems evolution (Lee, J., Ghaffari and Elmeligy, 2011).

3 Methodology

The works presented in the literature review provide alternatives for solving the challenges of the implementation of data-driven maintenance systems. The following framework combines successful approaches into a generic pathway.

STEP 0 – Definition of maintenance strategies, including the level of onboard automation, dependency of expert evaluations, available bandwidth, real-time monitoring or periodic data transferring. Works such as (Han and Yang, 2006) and (J. Zhao *et al.*, 2013) demonstrated low bandwidth requirements and low dependency of expert evaluations when the onboard system communicates with a shore fleet technical management centre using mobile network to transfer periodic status of the ship. Even lower requirements would be needed if all the following steps were physically installed onboard and only information about maintenance schedule were sent to shore base.

STEP 1 – Data acquisition and pre-processing – the acquisition of raw data can come from sensors, PLC or Integrated Automation System platforms. If the ship does not have an IAS or any kind of Supervisory Control and Data Acquisition (SCADA), which allows for easier extraction of data, the PLCs and sensors can be integrated via wireless network, as suggested by Michala and Lazakis, (2016), providing relative low installation costs. The pre-processing comprise the steps of cleaning and data analysis, as proposed by (Ellefsen *et al.*, 2019), using methods such as amplification, data compression, data validation, denoising and filtering, to extract the representative regime to be considered in the failures and faults detection. The data pre-processed onboard will be the input of the next step.

STEP 2 – System prognostics and failure prediction – the pre-process output might have problems of imbalanced and missing data. The first was aborded by (Behera and Misra, 2021) who suggested a combination of CGAN and DGRU approaches, while the second was investigated by Velasco-Gallego and Lazakis, (2020, 2021a, 2021b), who concluded that ARIMA was the best univariate imputation technique for stationary data, KRR worked better for large gaps of type MAR, and GA-ARIMA had best results with MCAR context. Prognostics can come from OEM manuals, expert opinions or by verifying the correlations between sensors, as demonstrated by (Jimenez, Bouhmala and Gausdal, 2020) using the software R®.

STEP 3 – Maintenance definition – Having evaluated the conditions of the systems and predicted their failures, the maintenance tasks can be defined from OEM manuals, expert opinions, or using AI in case-based models to verify suggestions for interventions, as proposed by (Behera and Misra, 2021) and (Han and Yang, 2006). In this case, expert opinions may still be needed to solve ambiguities rose when few solutions match the current problem.

STEP 4 – Support decision systems – As pointed by (Hodor, 2018), an enterprise asset management system (EAMS) compiles digital maintenances into a single system able to help operators to prioritize and plan maintenance. Commercial solutions as proposed by (Huang *et al.*, 2005) divides the problem into an application for working from the data acquisition to the maintenance definition, and other for attending as business platform, which synchronizes the maintenance needs to other company's dimensions. In this sense, (Cullum *et al.*, 2018) proposed a Risk-Based Maintenance (RBM) to schedule maintenance dynamically using risk assessment as a trigger. The works of (Tavakoli, Mousavi and Komashie, 2008) and (Lafond *et al.*, 2021) proposed DES models able to represent digital twin of physical systems which respect the constraints that will define the maintenance activities. This step requires a proposition of an enterprise maintenance management system that suits the company's necessity and culture.

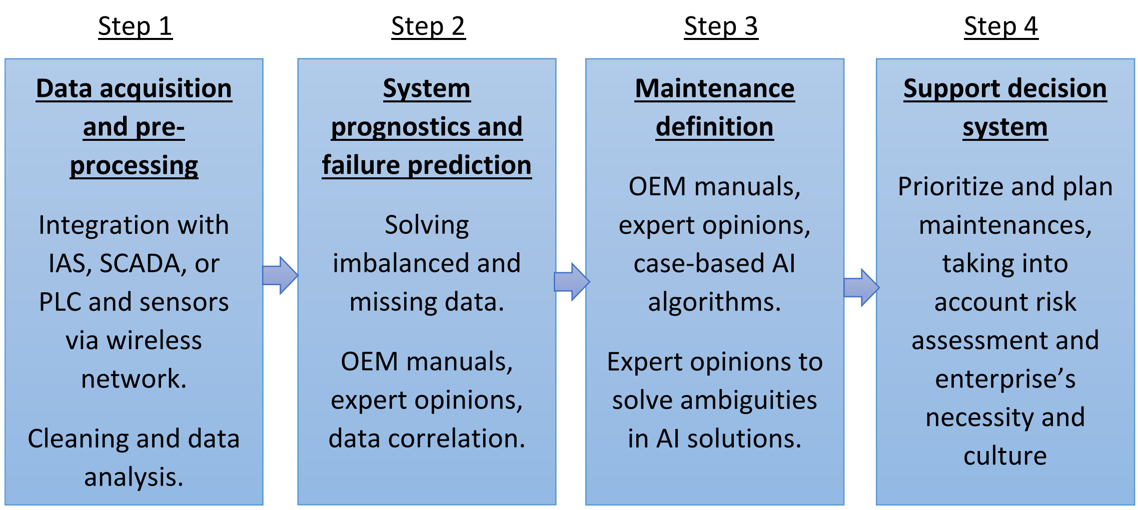

Figure 4. Framework for implementation of digital maintenance systems.

3.1 Management plan for modern maintenance systems

Considering CBM as one of the tools that should compose a bigger maintenance structure to support the overall company strategy, the management model should focus on the step 4 of the proposed framework. The model receives the maintenance definitions from previous applications that can include prediction algorithms, AI techniques for prognostics, and myriad of data acquisitions and processing data approaches. The proposed model is based on DES and has the potential to woks as digital twin of physical systems of the ship.

The DES model was based on a maintenance database for a tender vessel of the Brazilian company. The database included planned preventive maintenances, which were described in terms of periodic tasks recommended by OEM manuals, and unscheduled corrective maintenances that could possibly arise during the ship's life. For the sake of the simulation, the corrective maintenances were scheduled as random events around the mean time between failures (MTBF) of equipment parts. Both types of maintenances were inputted into the model as entities at the beginning of the simulation. Their attributes were assigned by reading a ".csv" file with the information according to presented in table 1.

The initial schedule of maintenances was stored in an attribute called estimated time to failure (ETTF), and as long as the simulation time approaches ETTF, the respective maintenances were sent to the process plan where it will evaluate the feasibility of their execution and the impacts they cause into the ship operation. The DES framework is presented in figure 5.

It is worth to notice that one of the aims of CBM is to eliminate the randomness of the corrective events, and to properly schedule them as preventive maintenance to avoid breakdowns, according to the condition of the equipment. Another aim of CBM would be to reschedule preventive maintenances which need to be anticipated to avoid breakdowns, or which be interesting to be postponed, thus providing more useful operating hours to the corresponding equipment, and potential savings along the ship's lifecycle. Therefore, to translate both aims into the model, the decisions from CBM analysis and predictions would result in a new .csv file that would update the initial schedule.

When corrective maintenances are removed from the storage, they directly affect an equipment by setting it to failure status. However, a breakdown of the ship only occurs if some specific combinations of maintenance attributes and ship operation conditions are observed. For instance, if it happens a maintenance of Failure Mode and Effects Analysis (FMEA) type 1, which needs to stop the system to be undertaken (Op_Inop equals zero), it means that a critical equipment had a breakdown and it interrupts the operation of the ship until the maintenance is done. A variation of this example would be a failure of an equipment with FMEA 2 which has already lost its redundancy due to other failure in the system, thus behaving as FMEA 1. Another scenario arises when, for instance, the ship is at sea and it is triggered a corrective maintenance of a critical system, which requires the ship to be at the port or it is only performed by shipyard personnel, it means that the ship needs to stop the operation at the sea and goes to port to attend the maintenance. In this case, the ship returns using its own propulsion or, depending on the severity of the breakdown, the ship may require to be towed. For simplicity of the model, the way the ship would return to port was simulated as a random delay of a week-time mean. The combinations of attributes and situations that trigger a ship breakdown are shown in figure 6.

Another dimension is given by the period of maintenance. According to the resolution MSC.204(81), (IMO, 2006), of the International Maritime Organization (IMO), which amended the International Convention for the Safety of Life at Sea (SOLAS) (IMO, 1974), it must have a minimum of two inspections of the outside of the ship's bottom during a five-year period. These inspections are normally undertaken in a dry-dock, according to IMO resolution A.1053(27), 2011, unless the ship applies for an in-water survey in lieu of bottom inspection in dry-dock to permit one dry-dock examination in any five-year period, (MSC.1/Cir. 1348, (IMO, 2010)), or the ship is enrolled in an Extended Dry-docking Scheme, according to the International Association of Classification Societies (IACS) recommendation No. 133, (IACS, 2013), which foresees conditions for a permission to carry out two consecutive in-water surveys during the renewal period of five years in an interval that not exceed 36 months, which allows the dry-docking inspection to happening in a period of 7.5 years. Therefore, the two normal inspections in a dry-dock are usually named as intermediate and major surveys, or intermediate and major maintenance periods, respectively. Nonetheless some manufacturers and shipowners stablish specific maintenances for these periods.

Preventive maintenances do not cause unintentional breakdowns, therefore, when the ETTF of a preventive maintenance comes up, and the ship is not able to shut down the related equipment or it is not at the right operation condition or maintenance period, the maintenance is held until all requirements are matched.

Apart from the required competent personnel that must be available, in quantity (attributes NrSkill1 and NrSkill2) and skill (Skill1 and Skill2), there are particular constrains that arise from spatial relationships as pointed by (Lafond *et al.,* 2021). The model herein proposed considers the working area capacity of ship compartments and a list of before-though affected compartments which were set as the attributes (COMP1, COMP2, and COMP3).

While FMEA type 1 can impact the operation at sea, the FMEA types 1 and 2 can impact the time that the ship spends in port due to an assumed policy of not allowing the ship to go to sea with a critical system, or its redundancy, having a maintenance due. Therefore, if a planned period in port was not enough to complete all maintenances of FMEA type 1 and 2, the ship will be delayed.

The model can also schedule opportunistic maintenances based on useful criteria such as the anticipation of specific maintenances of interest. As a default, the model schedule opportunistic maintenances, basically of FMEA type 3, when it happens a delay in port due to not-finished FMEA 1 and 2 maintenances.

Table 1. Maintenance attributes

<table>
<tr><th>Symbol</th><th>Description</th></tr>
<tr><td>Corr_Prev</td><td>0 – Corrective maintenance – Unscheduled action.
1 – Preventive maintenance – Periodic prescribed inspection/servicing based on elapsed time or hours of operation.</td></tr>
<tr><td>FMEA</td><td>1 – Failure will render the function inoperable and the function is involved in safety of the crew and the shipboard personnel or the function is involved in the ship main operation.
2 – Failure:
- Will not render the function inoperable (redundancy) and the function is:
- involved in the safety of the crew and shipboard personnel, or
- involved in the ship main operation,
- Will render the function inoperable (no redundancy) and the function is not:
- involved in safety of the crew and shipboard personnel, or
- involved in the ship main operation.
3 – Failure will not render the function inoperable and the function is not:
- involved in safety of the crew and shipboard personnel, or
- involved in the ship main operation.</td></tr>
<tr><td>Main_Priority</td><td>Priority given to maintenances due to company policy, which is related to FMEA and corrective / predictive characteristics, as the following:
Corrective: FMEA 1 – Priority 1; FMEA 2 – Priority 2; FMEA 3 – Priority 5
Predictive: FMEA 1 – Priority 3; FMEA 2 – Priority 4; FMEA 3 – Priority 6</td></tr>
<tr><td>Op_Inop</td><td>0 – System inoperable during performance of the maintenance task. The system is not available to perform all normal operations.
1 – System operable during performance of the maintenance task. The system is available to perform all normal operations.</td></tr>
<tr><td>Req_Ship_Condition</td><td>The required ship condition to realize the maintenance task, as follows:
0 – Any ship condition.
1 – At sea.
2 – Port.
3 – Drydock.</td></tr>
<tr><td>Req_Ship_Period</td><td>The maintenance is performed during the following scheduled maintenance period:
0 – Any period below.
1 – At sea.
2 – Port.
3 – Intermediate Maintenance Period (IMP).
4 – Long Overhaul (LOH).</td></tr>
<tr><td>Done_By</td><td>The maintenance is performed by staff from:
C – Crew.
V – Crew supervised by shipyard.
S – Shipyard.</td></tr>
</table>

Table 1. (continued).

<table>
<tr><td>Maintenance_cycle</td><td>Periodicity of the predictive maintenance task in hours</td></tr>
<tr><td>Op_h_Age</td><td>Periodicity base of the preventive maintenance tasks
0 – Operating hours.
1 – Age/elapsed time in hours.</td></tr>
<tr><td>MTBF</td><td>Mean Time Between Failures
The average time between two failures for an item in hours, adopted to calculate when corrective maintenances possibly occur.</td></tr>
<tr><td>TTR</td><td>Time To Repair
The average time expended (in hours), regardless of the number of personnel working simultaneously, required to perform a task.</td></tr>
<tr><td>Skill1</td><td>Type of staff resource composed by Done_By + Skill level + Skill speciality required for the maintenance task.
Skill level stands for:
B - Basic
A - Advanced
Skill specialities are:
ET - Technician Electronic
EL - Technician Electric
MO - Technician Mechanics
The combination of the above symbols gives the following list:
<table>
<tr><td>2 - CAEL</td><td>3 - CBEL</td><td>4 - CAET</td><td>5 - CBET</td><td>6 – CAMO</td><td>7 - CBMO</td></tr>
<tr><td>8 - VAEL</td><td>9 - VBEL</td><td>10 - VAET</td><td>11 - VBET</td><td>12 - VAMO</td><td>13 - VBMO</td></tr>
<tr><td>14 - SAEL</td><td>15 - SBEL</td><td>16 - SAET</td><td>17 - SBET</td><td>18 - SAMO</td><td>19 - SBMO</td></tr>
</table></td></tr>
<tr><td>NrSkill1</td><td>Number of skill 1 resource needed to execute the maintenance task.</td></tr>
<tr><td>HH1</td><td>Sum of human hours employed by all participating skill 1.</td></tr>
<tr><td>Skill2</td><td>A second skill required simultaneously in the same task.</td></tr>
<tr><td>NrSkill2</td><td>Number of skill 2 resource needed to execute the maintenance task.</td></tr>
<tr><td>HH2</td><td>Sum of human hours employed by all participating skill 2.</td></tr>
<tr><td>COMP1</td><td>A compartment of the ship affected by the maintenance task.</td></tr>
<tr><td>COMP2</td><td>A second compartment of the ship affected by the maintenance task.</td></tr>
<tr><td>COMP3</td><td>A third compartment of the ship affected by the maintenance task.</td></tr>
</table>

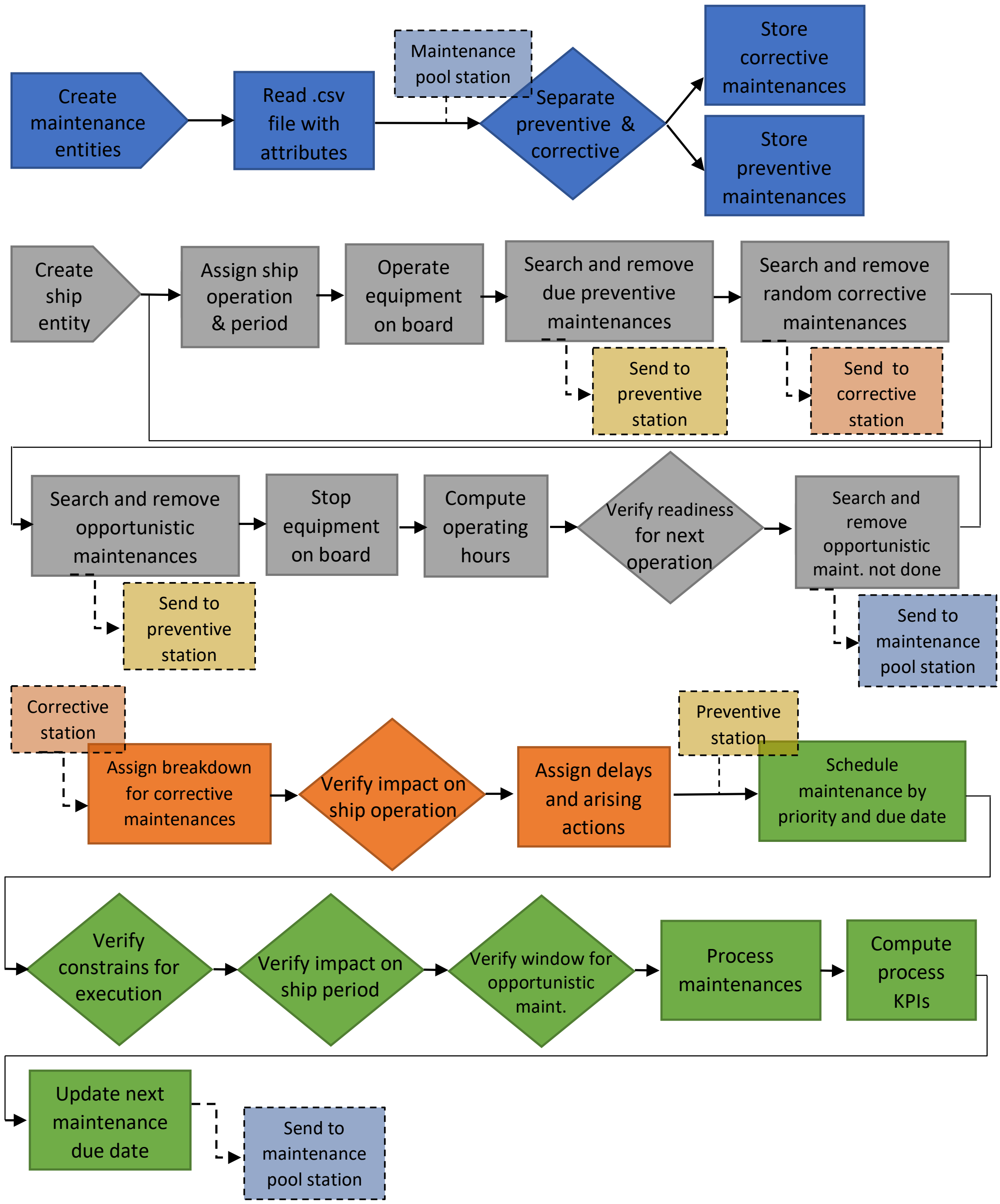

Figure 5. DES framework.

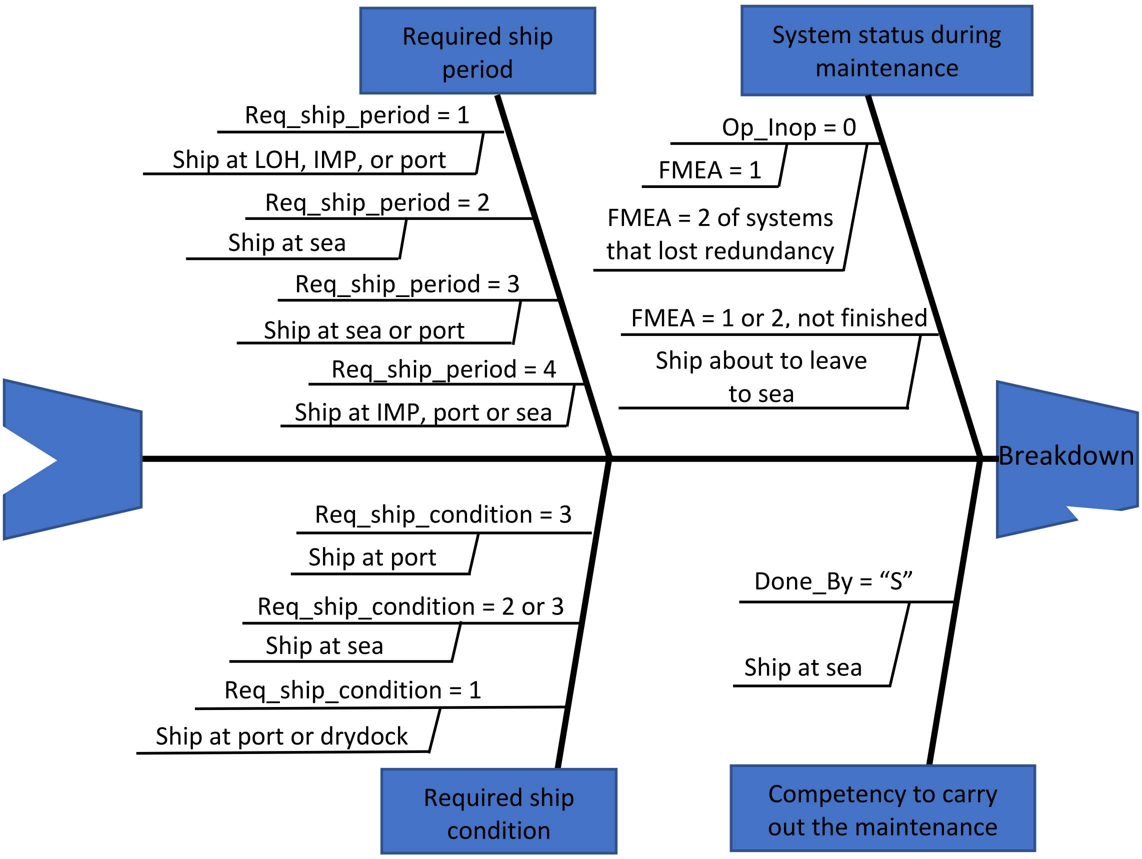

Figure 6. Combinations of attributes and situations that trigger a ship breakdown.

The aim of the model is to schedule the maintenances, by respecting the spatial constraints, and to provide a level of workload resulting from the schedule. Therefore, the number of personnel resources were set as infinite, while it will be actually restricted by the compartment working area capacity. Then, the calculated schedule is only possible if the workers from the ship's crew and the shipyard's personnel can use simultaneously the compartments respecting their limitations. The figure 7 shows the deck plans of the ship, with some compartments in red to represent examples of constrained capacity to host more maintenances. Thus, the model is useful for the company evaluating the required crew number and making better maintenance contracts with shipyards by setting the most economical number of regular workers, since the model calculates the required extra human-hours costs resulting from the selection of regular workers.

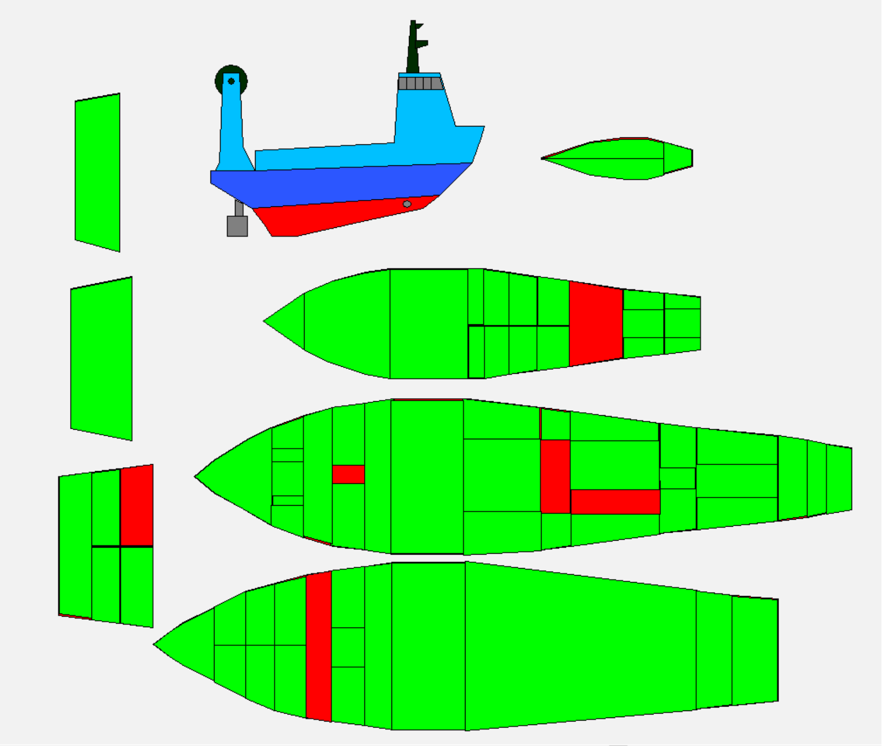

Figure 7. Ship deck plans with constrained compartments shown in red.

The number of regular workers trades-off not only with the cost of human-hours, but also with the worker's utilisation, which tends to drop with the increasing in the number of regular workers, and the resulting ship's cumulative availability, which tends to grow with the increasing in regular workers.

When extra workers are required, the cost of human-hours is elevated by an extra factor, adopted as 1.5 times the normal human-hour cost. Moreover, there is a significant cost related to the administrative burden of hiring and terminating extra workers, which were assumed as equivalent to 40 human-hours. These adopted values can be adjusted to the company's reality or can be investigated in a sensitivity analysis. However, they were set as constant for the simplicity of the model. Other key performance indicators (KPI) are the average number of extra hirings and the average period with extra workers, which convey an average quantitative meaning for the effort of hiring extra workers every time that it is required, and they are complemented by the KPI Number of extra hirings. The table 2 summarises the KPIs monitored by the model.
The model investigates the scenarios of eight hours of working shift, two shifts of eight hours, and a scenario of variable shifts, which starts with one eight-hour shift and changes to two eight-hour shifts if the workload surpasses the number of regular workers.

Table 2. List of KPIs calculated by the model

$$Utilisation_i = \frac{Cumulative\ time\ of\ human\ resources\ busy_i}{Total\ working\ available\ time}$$

$$Number\ of\ extra\ hirings_i = \sum_{0}^{total\ \ time} Events\ that\ required\ extra\ hirings_i$$

$$Extra\ workers_i = Number\ of\ workers\ that\ exceeded\ the\ regular\ workers\ in\ an\ event_i$$

$$Average\ number\ of\ extra\ hirings_i = \frac{\sum Extra\ workers_i}{Number\ of\ extra\ hirings}$$

$$Period\ with\ extra\ workers_i = Time\ betwen\ hiring\ exta\ workers\ and\ when\ they\ are\ not\ needed\ anymore_i$$

$$Average\ period\ with\ extra\ workers_i = \frac{\sum Period\ with\ extra\ workers_i}{Number\ of\ extra\ hirings_i}$$

$$Cost\ of\ regular\ workers_i = \sum months\ \times 160 \frac{hours}{month} \times Regular\ workers\ per\ shift_i \times Number\ of\ shifts$$

$$Cost\ of\ extra\ human\ hours_i = Extra\ factor \times\ (HH_1 + HH_2)_{Extra\ \ workers\ \ i}$$

$$Human\ Hour\ Cost_i = Cost\ of\ regular\ workers_i + Cost\ of\ extra\ human\ hours_i$$

$$HH\ \&\ Adm.Cost_i = Human\ Hour\ Cost_i + Adm.Cost\ \ \times Number\ of\ extra\ hirings_i$$

$$Downtime\ in\ period = \sum Breakdown\ time + Time\ delayed\ in\ period\ due\ to\ critical\ maintenances$$

$$Period\ Availability = \frac{Total\ time\ in\ period - Downtime\ in\ period}{Total\ time\ in\ period}$$

$$Ship\ Cumulative\ Availability = \frac{\sum Uptime\ at\ sea + \sum Uptime\ at\ port}{Total\ time\ of\ simulation}$$

Where:

$$i = Regular\ workers\ per\ shift\ ([1, 5, 10, 15, 20, 25, 30, 35])$$

$$Extra\ factor = 1.5\ (cost\ factor\ for\ extra\ hours\ hirings)$$

$$Adm.Cost = 40\ hours\ (cost\ in\ hours\ for\ hiring\ and\ terminating\ extra\ workers)$$

4 DES model results

Considering the case where only the planned preventive maintenance occurs it is possible to verify the workload profile of Figure 8, plotted for the first 8 years of ship's life. Most of the time there is low demand for workers with peaks between 10 to 20. Since preventive maintenance is periodic, there are few high peaks at the beginning of the life, while more peaks relative to maintenance with longer periodicity are added with time. The ship periods 3 and 4 (intermediate and major maintenance periods) concentrate more workers, and for longer periods. The availability of the ship is presented in figure 9. It was considered that the ship starts its life with 100% of availability. The critical maintenances and the circumstances that lead to downtimes reduce the availability of each period, which are reflected in the cumulative availability. The periods in dry-dock cause the bigger reductions.

The first scenario shows part of the intended life cycle of the ship, which is disturbed by random corrective maintenances, as presented in figure 10. These maintenances increase the number and the height of workload peaks, and consistently affects the availability of the ship, as shown in figure 11. Although the efforts of the company to select equipment with MTBF that coincide with the maintenance periods, the randomness of the failures may change the plan, and cause interruptions to ship operation, which the respective responsive actions may be taking the ship to port or to dry-dock. The figure 12 shows the interruptions that might happen due to stochastic failures. In this scenario, it was observed two intermediate periods which started around 30,000h and 32,000h, respectively. The first was caused by a corrective maintenance that required the ship to go to dry-dock before planned, and, because there were maintenances about to be due, the period accumulated many maintenances until the ship was free to go to sea. The second intermediate period happened in its ordinary time, according to the statutory requirements, which had low demand for workers in the end of the period because many maintenances were done before planned. This is a very undesirable scenario that puts the ship unavailable much longer than planned. Many companies seek for alternative solutions to avoid two close periods in dry-dock, such as underwater inspections and works, temporary repairs or operating with restrictions. These alternative solutions were not included in the model, but it was considered that CBM could indicate possible failures that cause interruptions, thus the interruptions were removed from the next scenarios.

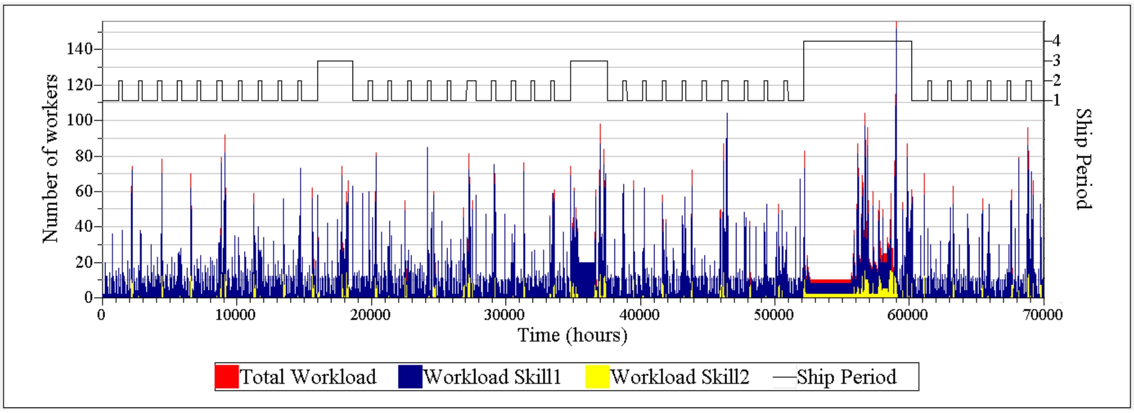

Figure 8. Workload profile of planned preventive maintenance (first 8 years).

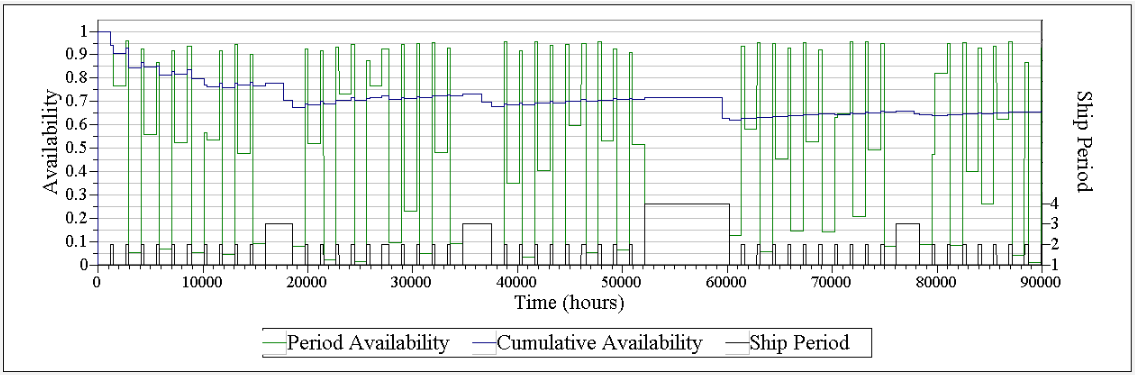

Figure 9. Ship availability of planned preventive maintenance (first 10 years).

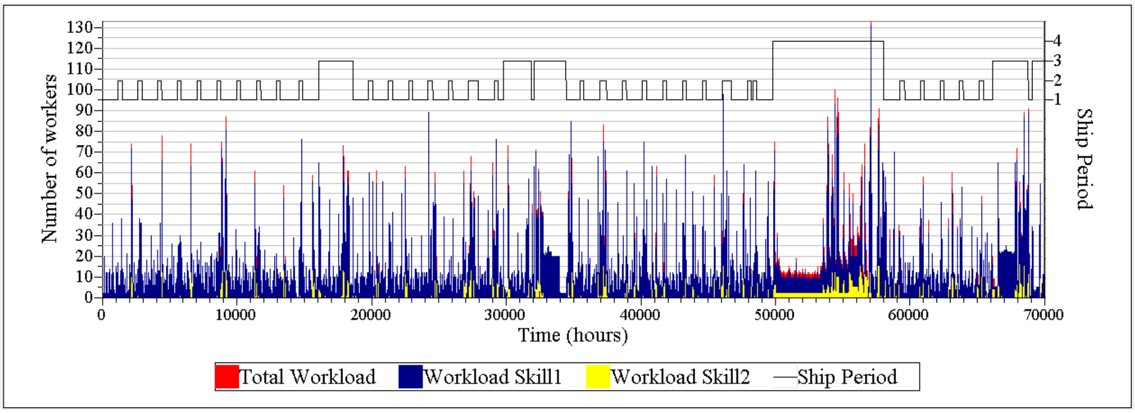

Figure 10. Workload profile of planned preventive and unplanned corrective maintenances (first 8 years).

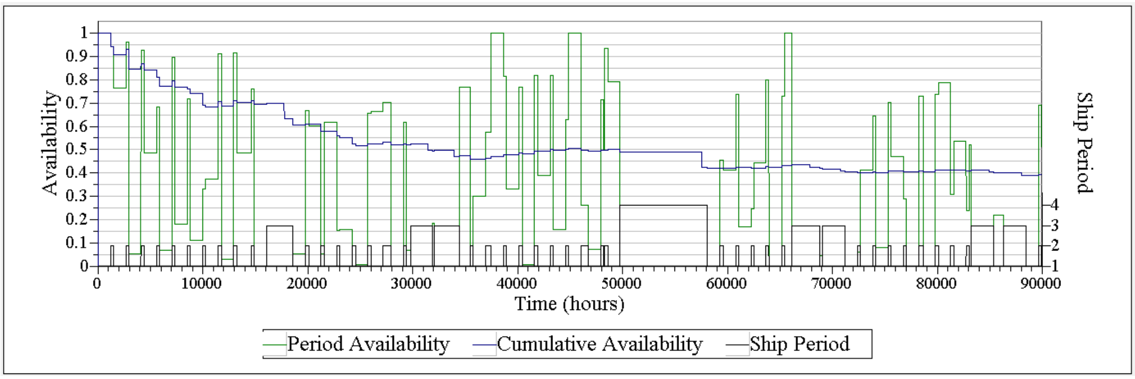

Figure 11. Ship availability of planned preventive and unplanned corrective maintenances (first 10 years).

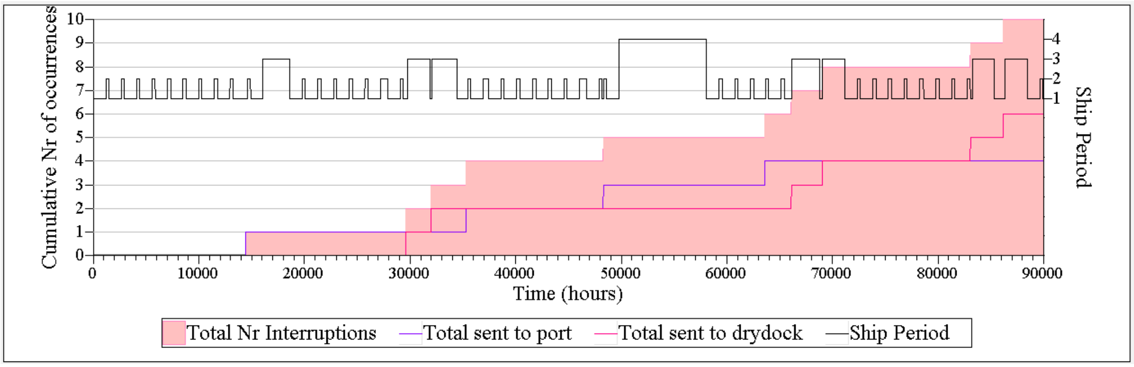

Figure 12.Interruptions of ship operations (first 10 years).

The high peaks in workload graphs are the results of the concentration of simultaneous due maintenances. Some of these peaks happened at the beginning of the period, which means that the maintenances were due before the period started and they were "waiting" for the ship changing to the required condition. If the regular workers were limited to a certain capacity, some peaks could be distributed across the period without delaying its end. However, when a peak is created after the beginning of the period, any limitation in the number of workers would result in delaying the end of maintenance period. The figures 13 and 14 show the workload profile and the availability of the ship for an example of 20 regular workers with no extra hirings. While the workload graph has many more peaks than the other scenarios, which conveys higher utilisation, the availability graph presents much less peaks of high availability, which means that the ship spent more time with critical maintenances due and she might operate with bigger backlog of non-critical maintenances. The cumulative effect of delays also reflected the number of times that the ship went to sea between 40,000h and 50,000h, which were two times less than the planned scenario.

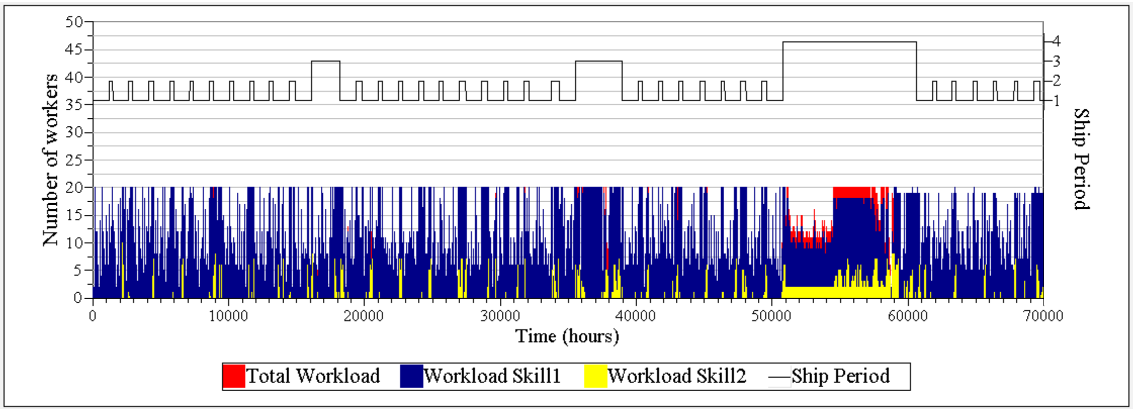

Figure 13. Workload profile of 1 eight-hour shift and 20 regular workers with no extra hirings.

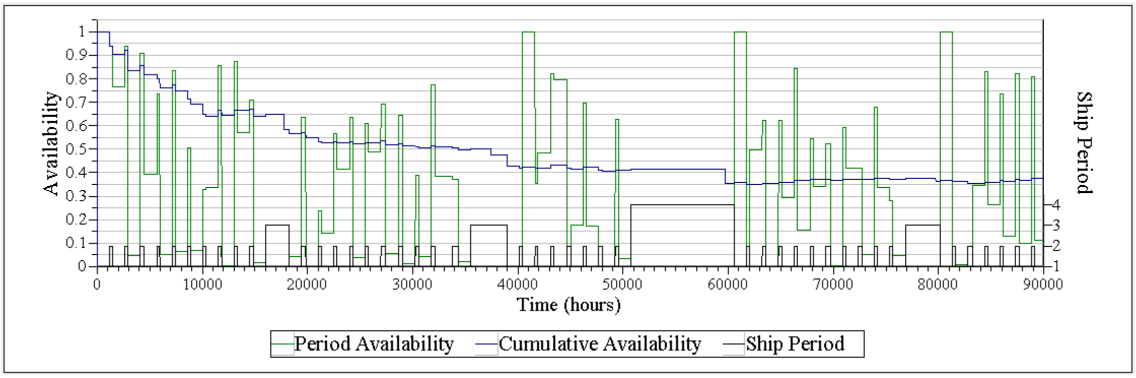

Figure 14. Availability of 1 eight-hour shift and 20 regular workers with no extra hirings.

The DES model was run for five scenarios. The first three had the number of workers resources only constrained by the capacity of compartments and it was allowed extra hirings. There were variations of one and two shifts of eight hours of work, and a variable shift condition, which consisted of changing from one to two shifts if the number of required regular workers exceeded the actual considered number. The last two scenarios were calculated for one and two shifts of work, with fixed number of regular workers, and no extra hirings were allowed. The last two scenarios were run from 15 regular workers to satisfy the minimum workers required to perform some of the maintenances.

Figure 15. Utilisation (left) and Ship cumulative availability (right) (first 10 years).

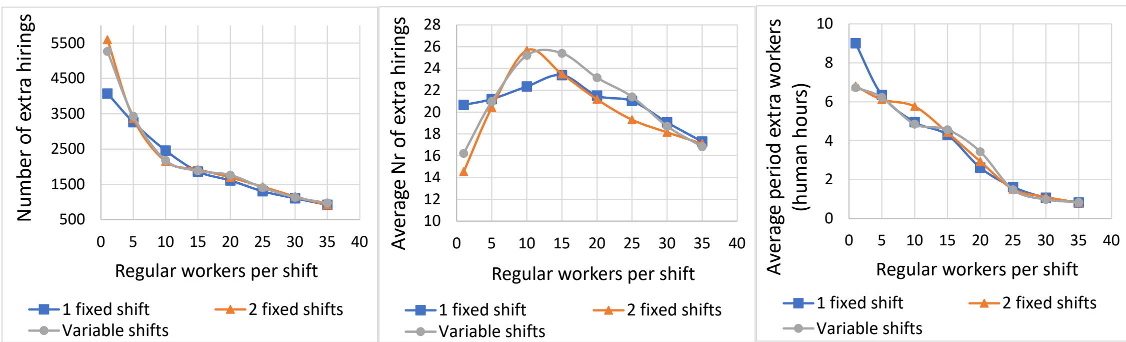

Figure 16. Number of extra hirings (left), Average Nr of extra hirings (centre), and Average period of extra hirings (right).

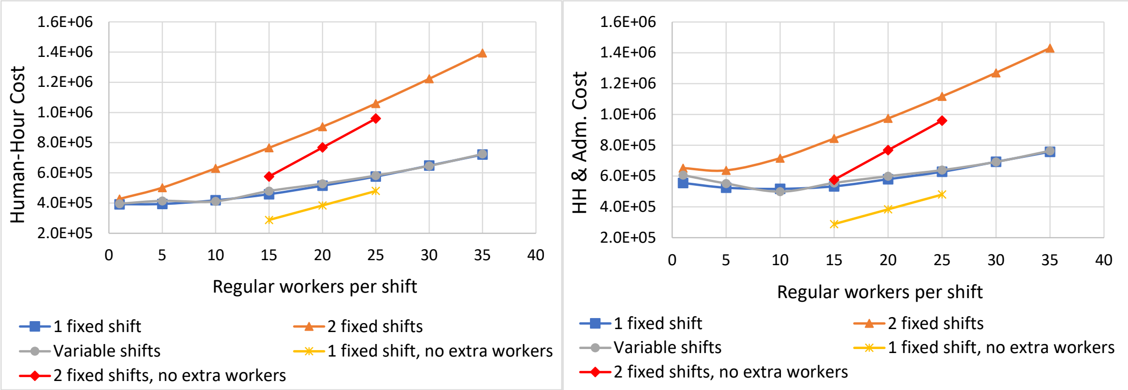

Figure 17. Human-hour Cost (left) and Human-hour with Administrative Costs (right) (in human hours).

5 Discussion

The trade-off between utilisation, availability, and human-hour costs, were pronounced by the number of shifts and the number of workers, including if extra workers were allowed or not. The higher the number of regular workers, the lower the utilisation, and the higher the cost. However, the availability is mostly affected by the number of shifts and the extra workers. The fixed shifts provided constant availability, because it was considered unlimited number of workers thus the time to repair was the only attribute that drove the availability, while the variable shift scenario oscillated with the number of workers. As a result of limiting the regular workers, the utilisation considerably increased but it was reflected in the ship´s availability, which consistent dropped with the delays occurred.

There is not an optimal solution for the number of regular workers since the company must decide what KPI is more important. If cost and utilisation were prioritized, the scenario of 15 regular workers and no extra hirings would provide the lowest cost and highest utilisation, but also the lowest availability of the ship. The scenario of 10 regular workers with variable shifts has the second lowest cost, but it requires a considerable number of extra hirings, which brings a managerial burden that can easily degrade the costs if the administrative costs were higher than considered for this model. A balanced scenario seems to be none of the five presented here, but some derived from a scenario of around 15 regular workers in a variable shift scheme that considers some extra workers in such conditions that suit the company’s administrative capacity.

The proposal of a DES model to schedule maintenance succeeded in dealing with many variables that arise from maintenance requirements, ship operational profiles, and spatial constraints. It provided prediction of KPIs for different number of workers and allowed for better understanding about the required number of ship crew and shipyard personnel by evaluating their utilisation and costs, and observing the trade-off with ship availability. The DES model aligns with the state-of-the-art for decision support systems intended in the step 4 of the proposed framework for data-driven maintenance management systems.

While some prediction and prognostic techniques attempt to reduce the dependence of historical data and try to find patterns by evaluating correlation among parameters or mounting case-based solutions, which may depend on some level of historical data, the proposed maintenance management plan depends only on the definition of maintenance attributes. However, populating the attributes with values may require good sources of OEM manuals, some hours of expert work, and probably depends on historical data too. On the other hand, when the maintenance attributes are fully filled, the only update required by CBM and prediction systems regards to the next scheduled time (MTBF or Maintenance_cycle attributes). The steps 1, 2 and 3 of the proposed framework for data-driven maintenance system include the infrastructure, algorithms and tools required for implementing CBM and prediction and prognostic systems to provide the maintenance definition and its attributes.

The number of maintenance attributes of the model may also need to include the impacts to other systems while undertaking the maintenances, such as shutting off electrical systems or closing water pipes, for instance. Some previous and post activities can be also included into the actual attributes, such as preparation of compartments, mounting scaffolds, installing forced ventilation, making health and safety inspections, installing tags and signs for hazardous activities, among other activities that may be specific for the ship. All these additions alter the DES model, which has the capacity to translate into new KPI numbers.

The model provides prediction for workload that is useful for sizing crew members and shipyard personnel. However, it was considered only the required hours for performing the maintenance tasks. The resulting workforce should include an extensive list of activities held onboard, as suggested by (Lee, John D., 1997). His work also provided guidance for validation of the workforce prediction. However, although he used five different validation approaches, the activities were based on shipboard tasks of tankships and freighters. Therefore, some adaptation from his data may be required.

6 Conclusions

This work gathered the challenges for the implementation of data-driven maintenance systems and presented the stat-of-art regarding the solutions found in current literature. Based on these solutions, it was proposed a methodology for managing data acquisition and a DES model for managing maintenance routine of ships.

The model potentially works as digital twin of the physical ship in term of maintenance management and has the capacity to explore “what if” scenarios, responding to variations in maintenance requirements, operational profiles, and spatial constraints, therefore providing maintenance schedule and prediction of KPIs for different number of workers. The model aligns with latest developments in decision support systems and offers better understanding about the required number of ship crew and shipyard personnel by evaluating their utilisation and costs, and observing the trade-off with ship availability.

7 Limitations of the study, recommendations, and future work

The DES model has the potential to work as digital twin of the physical ship, however, in this work, it was only considered the spatial constraint of the compartments. Other constraints also add complexities, such as the impact to other systems, the preparation and post activities, including health and safety aspects of the maintenances, logistics for materials and spare parts, for instance. The deck plans built here in two dimensions, could also be draw in three dimension to provide closeness to physical ship, which possibly would make it easier to visualize the spatial constraints.

Although it was foreseen in the model, the opportunistic maintenances had any special criteria for anticipation from forwards periods. The only opportunistic maintenances included were those scheduled during a breakdown. The works of Golbasi and Turan, (2020) and Budiono, Siswanto and Kurniati, (2021) shown that there is room for improvements of DES models when beneficial criteria for opportunistic maintenances are considered. The inclusion of logistic chains of materials and spare parts into the model could unfold criteria for anticipation of opportunistic maintenance.

Another limitation regards the FMEA attribute, since this work considered the lowest level, which refers to parts and equipment. The next level would be the FMEA evaluation of systems, which here was simplified as the level of redundancy. The systems or even higher levels could be included if the management plan was expanded to the fleet, embracing more ships in the model, which is other recommendation for future work.

The validation for the workload prediction provided by this work could not be done without comparing to real data, as proposed by (Lee, John D., 1997). Using the data that he found for tankships and freighters would lead to inaccurate validation. However, his methodology could be followed for collecting data from shipboard observations, structured interviews, analysis of planned maintenance logs and logbook data.

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Appendix – Summary of challenges and solutions presented in the literature review

Summary of challenges and solutions presented in the literature review

Challenge	Summary of the solutions	Reference
Lack of or little evidence of value for money and management´s lack of awareness	Translation of engineering data of physical systems and operations into continuous real-time cost function KPIs and common financial language.	(Psarommatis et al., 2022)
Lack of data standardisation, disjointed data and systems and lack of staff training on vessel and ashore	Identified key data elements to better exploit information about marine surface ship domain.	(Ford, McMahon and Rowley, 2013)
	Automated and integrated the accident/incident record keeping system with the PMS.	(Michala, Lazakis and Dikis, 2016)
	Suggested a Risk-Based Maintenance (RBM) to deal with the limitations of PM and RCM.	(Cullum et al., 2018)
	Scheduled maintenance dynamically using risk assessment as a trigger.	
	Provided a guidance to implement CBM$^+$, which is a concept developed by the USA DoD.	(Koons-Stapf, January, 2015)
	Identified elements of business/management (polices, doctrines and strategies) and technical categories (infrastructure of hardware and software, architecture for CBM$^+$, and data strategy)	
Hardware cost and installation time	Reduced installation costs based on wireless data transmission and implemented a novel decision support system (DSS) solution to be used onboard a ship with minimal initial training.	(Michala and Lazakis, 2016)
Bandwidth availability and cost	Applied communication technology such as 3G (WCDDA/CDMAEVDO/TD-SCDMA) and GPRS with lower cost, higher bandwidth, and satisfied coverage for ships on inland waterways.	(J. Zhao et al., 2013)
	Developed a fleet management centre system in a WEB application with information replicated both onboard of each ship and onshore.	

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Inability to analyse and make use of the data in real time	Proposed an architecture with capacity to self-organize the parameters in order of its importance, providing system status based on KPIs, and adaptive strategies to optimise the performance of systems in real-time.	(Fadzil, 2020)
Choosing data-driven maintenance approaches	Grouped hybrids approaches that uses data-driven methods to predict future conditions to be used in a model-based maintenance system.	(Liao and Köttig, 2016)
Defining input parameters	Grouped the countermeasures for breakdowns as reactive and proactive.	(Roosefert Mohan et al., 2021)
	Developed a predictive maintenance solution based on real-time monitoring and artificial intelligence using data from Integrated Automation System (IAS) of the ship, and automatically identifying the most important parameters that drive others through correlation analysis.	(Jimenez, Bouhmala and Gausdal, 2020)
	Developed a predictive maintenance for real-time data of lube systems.	(Roosefert Mohan et al., 2021)
Reducing the dependence of experts	Reduced or eliminated the dependence on the experts and replacing their involvement by prognostics and predictions algorithms.	(Ellefsen et al., 2019)
	Introduced and reviewed 4 deep learning techniques for implementing PHM to autoships.	
	Proposed a framework for the local maintenance (at the manufacturer venue) including a real-time condition monitoring system; fault diagnosis and degradation prediction modules; and database storage and presentation regarding maintenance strategy. Only relevant features should be transferred to maintenance centre for the experts solving ambiguities not managed by the proposed AI technique.	(Han and Yang, 2006)

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Lack of continuity or incompleteness of acquired data	Concluded that the ARIMA was the best univariate imputation technique for stationary data. For MAR data the KRR leads to better results for large gaps, while for MCAR context GA-ARIMA, which is an association of a Genetic Algorithm to determine the coefficients of ARIMA, had better results.	(Velasco-Gallego and Lazakis, 2020), (Velasco-Gallego and Lazakis, 2021a), (Velasco-Gallego and Lazakis, 2021b)
Unavailability of fault-data	Used CGAN to augment data of fault diagnosis to balance the missing data in the acquired sample, and combined with DGRU to perform RUL predictions.	(Behera and Misra, 2021)
Simulating physical world using real-time-data	Proposed an architecture composed by Data Integration and Processing and Simulation Modeling Engine, which provide flexible acquisition of any type of input, and simulate the physical environment in a model that reacts to real-time events using DES model.	(Tavakoli, Mousavi and Komashie, 2008)
Implementing CBM to old assets	Criticised initiatives based only on historic data of past failures without combining with observed CBM data. Suggested the use of supervised or unsupervised machine learning together with company's insights regarding to the following actions after a failure prediction.	(Hodor, 2018)
Implementing CBM to old assets	Proposed enterprise asset management system (EAMS) that consolidate and integrate all information into a single system able to help operators to prioritize and plan maintenance.	(Hodor, 2018)
Implementing CBM to old assets	Suggested lake ecosystems over warehouse types of big data, because data lakes are open source, do not need structured data, and are mostly applied to predictions and prescriptions of internal and external sources of data.	(Hodor, 2018)

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Techniques for modelling maintenance management systems	Used DES for modelling the physical system and reproducing the chain of events ruled by maintenances attributes and company's constraints to propose a maintenance decision support model.	See list on page 15.
Dealing with geospatial constrains	Proposed model-based AI, heuristic methods and DES to schedule project tasks observing attributes such as priority, precedence relationship, resources required, time required, working area required, proximity impacts, path impacts.	(Lafond et al., 2021) & (Bertrand, 2020)
Defining required workload	Demonstrated the impact of opportunistic maintenances and urgent defects in the workload necessity of warships maintenance using DES framework.	(Schütze and Hughes, 2012)
	Proposed a methodology for validating shipboard workforce prediction	(Lee, John D., 1997)
Future maintenance management systems	Proposed an intelligent maintenance system composed by two commercial applications, Watchdog Agent^{TM} and Device-to-Business (D2B^{TM}). The applications are responsible for monitoring and predicting the progression of a fault and autonomously, or with some human aid, triggering maintenance schedule and asset management decisions or actions. The aim of this system is to optimize maintenance schedule, eliminate the unnecessary and costly preventive maintenance, and reduce costs by optimizing resources allocation and reducing lead-time for spare parts.	(Huang et al., 2005)
	Suggested that PHM is a stepstone for achieving resilient, self-maintenance and Engineering Immune Systems (EIS), which are fault-tolerant systems.	(Lee, J., Ghaffari and Elmeligy, 2011)