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Revolutionizing Planned Maintenance in Maritime Industry: Leveraging Artificial Intelligence and Enhanced Stakeholder Communication

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Abstract

The marine sector is on the verge of a technological revolution, with Artificial Intelligence (AI) poised to alter planned maintenance methods. Modern vessels are becoming more and more inefficient with traditional maintenance procedures that rely on manual input and repair list analysis, which might result in errors. These procedures can be made more efficient by utilizing AI. For example, repair lists can be automatically evaluated and integrated into Planned Maintenance Systems (PMS) with only one click, thereby decreasing the amount of manual labor and improving accuracy. AI's predictive powers not only simplify data integration but also enable proactive maintenance scheduling. AI can predict which materials are likely to need revamping by examining past material utilization, ensuring readiness and reducing downtime. This kind of foresight improves operating efficiency and vessel reliability in addition to optimizing resource allocation. Furthermore, AI, when combined with Large Language Models (LLM), enables real-time communication with stakeholders by producing detailed reports on vessel status, including maintenance tasks and material availability. Because of this transparency, management is able to act quickly and decisively, ensuring that all operational levels are strategically aligned. AI integration into maritime maintenance is a revolution rather than merely an improvement. The marine sector may attain unparalleled levels of efficiency, safety, and competitiveness by integrating artificial intelligence (AI) into fundamental maintenance operations and communication tactics. This study lays the groundwork for a more intelligent and robust future by providing a thorough framework for integrating AI into maritime planned maintenance.

Keywords
Artificial Intelligence, Maritime Industry, Planned Maintenance, Predictive Analytics, PMS, Operational Efficiency, Stakeholder Communication

1.Introduction

Historical data on material replacements required for predictive maintenance strategies is crucial for the upkeep of marine vessels and installations designed for long sea voyages. Lists of tasks and spare parts are meticulously planned during the vessel's design, including both dry docking repairs and onboard tasks like inspections and fluid sampling. However, the lack of an automated system to gather and integrate repair data causes inefficiencies in the maintenance process. By automating the data collection and reporting process, the maintenance process can be streamlined, allowing for more advanced predictive maintenance strategies to be implemented.

Artificial intelligence generally refers to other-than-human (or rather, other-than-animal) intelligence, mostly in the form of a computer program. In a broader scope, it can mean any form of automation of knowledge work, such as maintenance planning. In a narrower scope, it can mean neural networks and other forms of machine learning that utilize data and statistical methods to find patterns and learn from them. Such techniques would be suitable for maintenance procedures, as they often involve repetitive actions based on vast amounts of information, with much of the information flow being implicit or not fully translatable into rules, thus making automation difficult with traditional rule-based algorithms. Here, an overview is provided of the background of planned maintenance in the maritime industry, its shortcomings, and how AI can help alleviate these issues. (Størkersen 2021)

1.1. Background of Planned Maintenance in the Maritime Industry

The maritime industry relies on a network of vessels for global trade. However, outdated systems and disconnected databases hinder operational effectiveness. The scheduled planned maintenance strategy is a key area that needs improvement. Previously, vessels operated on a time-based procedure, but the introduction of planned maintenance brought specific instructions for maintenance and inspections. Dry-docking maintenance, performed every 4-5 years, represented a significant cost for shipping companies. Studies estimate that 15-20% of operational costs arise from ship repair and maintenance, including dry-docking. Intermediate maintenance for instance, 52 week-plan activities are also necessary during a ship's operation.

1.2. Significance of Artificial Intelligence in Maintenance

The planned maintenance system serves to ensure the maintenance, inspection, and repair of vessels in a scheduled and systematic way. The aim is to achieve a high level of safety and reliability for vessels and their machinery. However, current procedures and methods used for planned maintenance in the maritime sector often lead to excess and unnecessary costs incurred by vessel owners. Keeping a fleet of vessels fully operational without too much downtime requires a structured maintenance schedule. This schedule is complex in its design and execution, and often requires expert knowledge to optimize it effectively. Many Maritime Maintenance Management Systems (MMMS) on the market today allow for planned maintenance scheduling, as well as providing information on the locations of equipment onboard vessels. However, planned maintenance is often carried out on large sets of spare parts for a single equipment item, or on sets of similar equipment items onboard. In these cases, no or very few factors are taken into account in designing the maintenance schedule, other than the period of time between the carry-out of maintenance on each item.

The aim of this thesis work is to address this challenge. Furthermore, many current MMMS solutions do not include the repair location of equipment, instead providing it only as textual input in the item description. A significant number of machinery parts also break down in more than one location onboard. Thus, the need arises for an integration of the repair list with the planned maintenance system, accounting for the locations of each equipment item. Through comprehensive analysis of available data concerning the equipment items and repair equipment locations onboard, a tool that generates a repair list for planned maintenance is developed. The resulting contribution is a clear step toward a more intelligent planned maintenance system that reduces downtime and thus costs incurred by vessel owners.

In planned maintenance, a number of aspects lend themselves to the study of artificial intelligence methods for process and cost optimization. Vessels often have a large set of similar equipment items, which are planned to be maintained on either short work-interrupting intervals or on their own failure. This often leads to high costs, both in terms of confined and uncaptured downtime, as well as in allocation of resources and assets for compliance with underdeveloped, inefficient procedures. With constraints on the number of available resources, shore-side and crew workload is also under pressure. This could lead to crew growth, and thus rising costs for vessel owners, as well as a reduction in quality and safety of key operations, such as maintenance. Hence, an initial step in reaching a holistic planned maintenance strategy with respect to artificial intelligence is outlined. First, common planned maintenance procedures on a small vessel and key areas where such methods could be utilized are provided, serving as a basis for a more intelligent planned maintenance management system. Then, an overview of artificial intelligence methods and approaches used in similar maintenance, inspection, and repair (MIR) applications is presented. Finally, a scoping study with respect to interaction between planned maintenance management systems and artificial intelligence-based methods is given, identifying key focus areas for further studies and development on the subject.

2. Current Challenges in Planned Maintenance

The planned maintenance of seagoing vessels is a large field consisting of many interconnected tasks. Each vessel has a planned maintenance program consisting of an interval, several tasks, and if applicable, a vessel system. These tasks consist of inspections, repairs, and replacements, which vessels must execute at certain intervals to continue sailing. A task must be initiated for a vessel at a certain point in time to ensure the ship is compliant with the maintenance program. When a task is initiated, the planned inspection or action must be performed on the vessel system, and a list of repairs must be produced detailing all the indications found to be not compliant with the given requirements. Both the inspections and generated repair lists consist of many interrelated processes that currently must be executed manually for every planned maintenance task for a vessel. (Johansson et al. 2021)

The planned maintenance repair lists consist of several pieces of relevant data, such as the subcomponent inspected, findings, repair action needed, followed by references in documentation if applicable. Each maintenance task is partly unique and executed once in intervals ranging from some months to several years. The number of tasks and generated repair lists is also a large number for bigger vessels. The amount of data can be very difficult to manage if repair lists between different vessels and equipment are also taken into account. Even though data production is so large, most data is still completely unutilized. Once a vessel's planned maintenance repair list has been issued, the repair list is used for the duration of the maintenance event. After completion, the repair list is stored, and if an indication similar to this one is found again, a similar process must be executed again even when it is known how to handle the indication beforehand. All the data is also spread out over various systems targeting certain applications. Communication between these systems is limited, and to process data needed at a certain point in time, configurations need to be made. If no configuration is made, the process must start from scratch given that all input information needed to execute the process is known by the operator. A different focus during design and implementation resulted in systems that do not fully work seamlessly together.

2.1. Manual Inspection and Repair Processes

Planned maintenance (PM) is vital for ensuring the smooth operation and longevity of vessels. To minimize unplanned stoppages and safeguard crew and asset safety, regular inspections are conducted. However, current inspection and reporting processes are predominantly manual. Inspectors record findings in different report formats and tools, such as handwritten notes, Excel lists, and photographs. These results must be manually integrated into existing databases, usually undertaken by administrative staff, and must be rectified multiple times due to logical errors or insufficient quality records. Even as newer digital tools are introduced, the trend of conducting inspections has not changed. This results in no improvement in those who conduct inspections and record findings, who still rely on lists recorded in pre-defined formats separated from the database. Consequently, decision-makers must first re-analyze a large number of reports before they can act on findings suggested by inspectors, frequently missing repair windows due to delays and misunderstandings. Inspectors also lack access to needed historical records for context, which could improve the efficiency of both inspections and repairs. Additionally, relevant findings from inspections conducted by other stakeholders are unknown and cannot be comprehended. [Wang et al. 2020]

(Peña Zarzuelo et al. 2020) A data-driven PM approach is feasible by providing PM with dynamic repair lists integrated seamlessly with an extensive database of contextual records and repair history complemented by expert-generated repair notes and hints. Aids for inspections would be provided for different onboard stakeholders with databases, records, lists, and findings commensurate with stakeholders' roles. Also, sensors would record both findings and necessary multimedia evidence to facilitate the subsequent assessment of recorded data. Replays of past inspections, analyses, and actions could be provided alongside existing aids. Such a system would transform PM into a semi-automated process with human involvement where necessary and thereby improve the informedness of decision-makers and the quality of inspection findings. Automated record retrieval and suggestion would improve the efficiency of all parties. With comprehensive onboard tracing of mechanisms, trends could be noticed and reasons understood, which would enhance vessel care quality.

2.2. Data Fragmentation and Integration Issues

To ensure the smooth operation of a vessel, machinery, systems, and equipment require appropriate and timely maintenance. Shipping companies must coordinate inspections, repairs, and renovations of multiple vessels across various geographical locations. Thus, a vast amount of data is created, including planned maintenance systems (PMS) data, maintenance actions (work orders), work process data, observations and notes (e.g., reported faults, missed tasks), spares inventory data, and repair history.

Additionally, classification societies and ship managers create repair lists and requests for repair jobs. However, such data is often fragmented and distributed across different vessels, systems, and databases, preventing its effective use to eliminate missed tasks, find systematic faults, or continuously improve maintenance activities. Data stored in different systems cannot be easily combined due to large differences in data structure, meaning, and format. Thus, to make the best use of the data in the vessel-wide context, its integration is necessary.

Additionally, currently collected data is often unrecoverable and easily lost in a manner which hinders its use for retrospective analyses. This is especially problematic with logged process data (monitoring signals, recordings), which is often not collected at all or inadvertently overwritten and removed from the systems. Thus, the proposed approach breaks "silos" by addressing data fragmentation and integration issues and creating a unified database of all relevant data from the vessel, which can then be brought ashore for more advanced data analyses.

3. Artificial Intelligence Applications in the Maritime Industry

Shipbuilders must swiftly adjust to these developments to prevent rising costs and remain competitive in an ever-evolving industry. By embracing these technological advancements, they can streamline operations, optimize resources, enhance crew training and safety protocols, and establish robust digital infrastructure to support smart decision-making. Additionally, AI-powered systems provide valuable insights into fleet management, route optimization, fuel consumption, and emissions reduction, enabling a more sustainable and environmentally friendly maritime sector. As the industry continues to evolve, collaboration between humans and AI will foster innovation, drive economic growth, and ensure the maritime industry remains at the forefront of technological breakthroughs. It is crucial for shipbuilders to invest in research and development, constantly adapting and incorporating emerging technologies to stay ahead of the competition and shape the future of the maritime industry.

3.1. Predictive Maintenance

In both industrial and maritime settings, the implementation of predictive maintenance recognizes the dynamic nature of equipment degradation, which is commonly characterized by a reduction in performance over time. Such methodology relies on the continuous collection of relevant data, coupled with the application of various analytical techniques in order to allow predictions regarding the equipment residual lifespan. Therefore, the predictive maintenance of assets or installations seeks to predict the remaining useful life (RUL) or time-to-failure of critical components. Successful predictions can facilitate scheduling repairs and avoiding unexpected failures proactively.

The foundation of any predictive maintenance implementation is the acquisition of relevant data over time, both incoming data from the equipment and, potentially, historical records. Accordingly, in a maritime context, data from various sources can be leveraged, including maintenance management systems such as Planned Maintenance Systems (PMS), in conjunction with relevant data from the shipping company. Such data can contain valuable information about major events related to equipment performance deterioration. The examination of the underlying causes of these events helps with prior knowledge generation necessary for predictive maintenance implementation.

4. Data Collection

More historical data about material replacement is needed for predictive maintenance strategies when comparing the use of LSTM, RNN, and XGBoost for an AI model to predict material replacement. Specifically, I am interested in 100 historical replacements for O-Ring. This data collection process involves meticulous organization and integration of repair recommendations and findings to facilitate the data mining process. To assist in this process, reputable class societies and major Original Equipment Manufacturers (OEMs) have developed cutting-edge autonomous machinery systems, known as fleet support solutions or real data platforms. These systems collect, analyze, and integrate real-time engine and vibration data, and embed repair list information into comprehensive reports to streamline the maintenance process. Additionally, third-party runtime models can be utilized to accurately predict breakdowns and create time series data for estimating maintenance intervals, contributing significantly to optimizing maintenance procedures for proactive and cost-effective measures. (Zonta et al. 2020), (Sahal & Breslin 2020), (Cheng et al. 2020)

5. Results and Discussion

5.1. The Analysis

This research will tap into the application of recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and the eXtreme Gradient Boosting (XGBoost) algorithm for predictive models, as RNNs and LSTMs are well-regarded and widely used for time series analysis while eXtreme Gradient Boosting (XGBoost) is a highly efficient, scalable, and accurate model, having demonstrated robust performance compared to other models. A dataset containing approximately 100 records of actual maintenance completion and the number of man-hours expended will be used to understand the predictability aspect and, more specifically, how timing may be assessed given specific sets of conditions up to four weeks before a ship arrives. **(**Dyer et al. 2022)

To meet the objective, RNNs, LSTMs, and traditional eXtreme Gradient Boosting (XGBoost) algorithms will be used to evaluate the 5 years prediction by 100 actual data of O-Ring of planned maintenance completion and, more specifically, the required number of man-hours. Three sequential models (one representing each of the ship's phases) will be trained to predict the maintenance completion task at the end of each phase for each ship. (Ouma et al. 2021), (Wei et al . 2021) 9, Pathan et al. 2021)

5.2. Validation

5.2.1. Mean Squared Error (MSE) Calculation Formula

The general formula for **Mean Squared Error (MSE)** is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Example of MSE Calculation for Each Model:
XGBoost

$$MSE_{XGBoost} = \frac{1}{100}\sum_{i=1}^{100}(y_i - \hat{y}_i)^2$$

$$MSE_{XGBoost} = \frac{1}{100}\left[(7080 - 7079.90)^2 + (6740 - 6740.34)^2 + (7020 - 7019.65)^2 + \ldots\right] = 53746.57$$

LSTM:

$$MSE_{LSTM} = \frac{1}{100}\sum_{i=1}^{100}(y_i - \hat{y}_i)^2$$

$$MSE_{LSTM} = \frac{1}{100}\left[(7080 - 6963.13)^2 + (6740 - 6959.11)^2 + (7020 - 6955.29)^2 + \ldots\right] = 120776.89$$

- **RNN**:

$$MSE_{RNN} = \frac{1}{100}\sum_{i=1}^{100}(y_i - \hat{y}_i)^2$$

$$MSE_{RNN} = \frac{1}{100}\left[(7080 - 6990.60)^2 + (6740 - 6991.03)^2 + (7020 - 6991.45)^2 + \ldots\right] = 119957.21$$

5.2.2. Euclidean Distance Calculation Formula

Euclidean Distance measures the distance between two vectors (the actual and predicted values) in an n-dimensional space. The formula is:

$$EuclideanDistance = \sqrt{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Example of Euclidean Distance Calculation for Each Model:

XGBoost:

$$EuclideanDistance_{XGBoost} = \sqrt{\sum_{i=1}^{100}(y_i - \hat{y}_i)^2}$$

$$EuclideanDistance_{XGBoost} = \sqrt{(7080 - 7079.90)^2 + (6740 - 6740.34)^2 + (7020 - 7019.65)^2 + \ldots} = 2318.33$$

LSTM:

$$EuclideanDistance_{LSTM} = \sqrt{\sum_{i=1}^{100}(y_i - \hat{y}_i)^2}$$

$$EuclideanDistance_{LSTM} = \sqrt{(7080 - 6963.13)^2 + (6740 - 6959.11)^2 + (7020 - 6955.29)^2 + \ldots} = 3475.30$$

RNN:

$$EuclideanDistance_{RNN} = \sqrt{\sum_{i=1}^{100}(y_i - \hat{y}_i)^2}$$

$$EuclideanDistance_{RNN} = \sqrt{(7080 - 6990.60)^2 + (6740 - 6991.03)^2 + (7020 - 6991.45)^2 + \ldots} = 3463.48$$

3. Predictions at Data Points 60 and 80

XGBoost:

$$Predictionatdatapoint80 : \hat{y}_{80} = 6889.88 Predictionatdatapoint60 : \hat{y}_{60} = 7079.90$$

LSTM:

$$Predictionatdatapoint60 : \hat{y}_{60} = 6963.13$$
$$Predictionatdatapoint80 : \hat{y}_{80} = 6949.64$$

RNN:

$$Predictionatdatapoint60 : \hat{y}_{60} = 6990.60$$
$$Predictionatdatapoint80 : \hat{y}_{80} = 6999.09$$

Here below is the table that represents calculations between each model by Final MSE, Euclidean Distance, and 2 sample predictions.

Table 1. Calculated Final MSE, Euclidean Distance, and 2 sample predictions

Model(s)	MSE	Euclidean Distance	Prediction at Data 60	Prediction at Data 80
XGBoost	53746.57	2318.33	7079.90	6889.88
LSTM	120776.89	3475.30	6963.13	6949.64
RNN	119957.21	3463.48	6990.60	6999.09

Table 1 and Figure 1 compare the performance of XGBoost, LSTM, and RNN machine learning models in predicting specific data points within a dataset. The primary metrics for comparing models are Mean Squared Error (MSE), Euclidean Distance, and the models' predictions at two key data points: data indices 60 and 80. Greater accuracy is indicated by higher values.

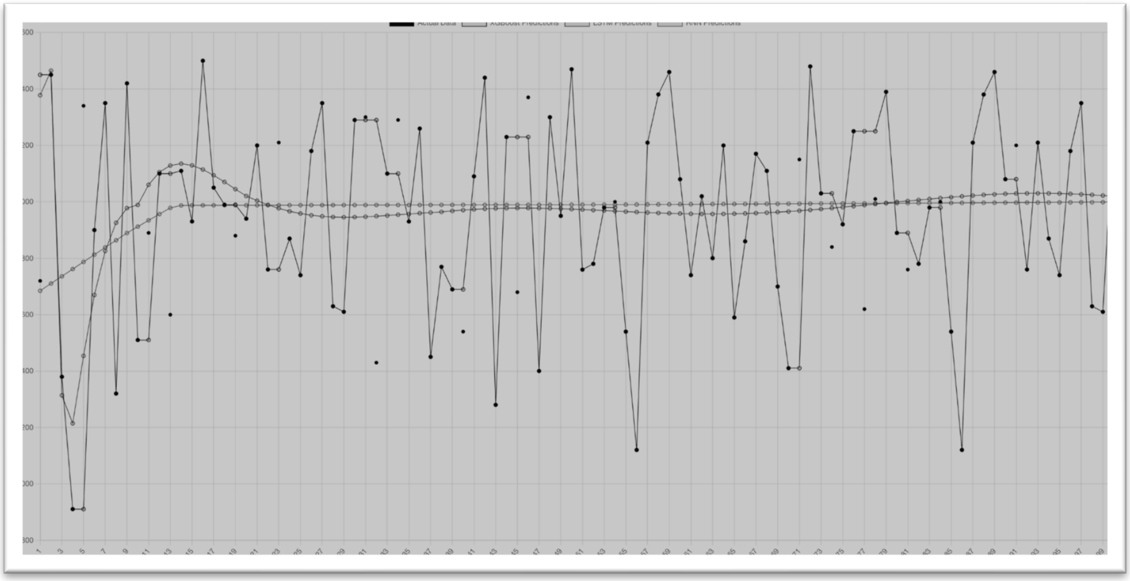

Figure 1. Machine Learning Calculation for 100 overhauled O-Ring

The MSE measure quantifies the average squared difference between actual and expected values. During this study, XGBoost showed superior predictive accuracy compared to LSTM and RNN, with the smallest MSE value being 53746.57. Similarly, the Euclidean Distance calculates a distance metric by squaring the differences between the expected and actual values and taking the square root of the sum.

The MSE metric measures the average squared gap between the predicted and true values, with reduced values suggesting greater precision. XGBoost outperformed LSTM and RNN in predictive accuracy by achieving the lowest MSE of 53746.57 in this study. Similarly, the Euclidean Distance calculates the square root of the sum of squared variances between the predicted and actual values, giving a comprehensive measure of distance. Once more, XGBoost achieved the highest accuracy with a Euclidean Distance of 2318.33, much lower than LSTM (3475.30) and RNN (3463.48), showing more accurate predictions.

The forecasts at data points 60 and 80 additionally demonstrate how well the model is performing at particular indices. When it comes to predictions at the points of 7079.90 and 6889.88, XGBoost is more accurate than the other models, showing its strength and reliability. On the other hand, LSTM and RNN demonstrate less accurate forecasts, with LSTM predicting 6963.13 and 6949.64, and RNN predicting 6990.60 and 6999.09 at these specific points.

In general, the table shows that XGBoost is the most successful model in this scenario, with lower error rates and more precise predictions than the LSTM and RNN models.

6. Conclusion

In this chapter, we aim to exploit the capabilities of AI in providing a comprehensive view of the overall failure problem and to suggest potential directions and related work in the maritime maintenance sector. The proposed system integrates a robust classification model with another predictive maintenance model to predict equipment failure, which will lead to minimizing a ship's unexpected mechanical failure. We highlight our direction by discussing our system in the context of the application points. Our future goals are to successfully carry out a real-world implementation of our system, building a strong learning framework in anticipation of service issues, and running over large data sets.

These can be like marine equipment and equipment register; fault report records, logbook records, and implemented maintenance.

Over the years, many applications explored the data pattern from ship logbook records and carried out maintenance logs, such as maintenance optimization, condition-based monitoring, and failure diagnostics, etc. As a survey, only a few reviewed those applications and considered them in a coherent survey covering all data pillars. Due to the lack of such a survey, few systems focus on advanced maintenance, and it is hard in research and application to introduce the proposed hints. In addition to introducing the systems - diagnostics, prognostics, and health management, health metrics, etc., marine-based suggestions are not considered for new entries. With the constant expansion of big data and the establishment of digital twins, to revitalize the enterprise's competitive advantage, we suggest that maritime systems revitalize the operations of a ship and its operator. There is a risk of ignoring the potential business value. Instead, understanding ship operations using data analysis, machine learning, and data visualization introduces knowledge. In the future, it will evolve to meet the requirements. Enterprise data learning has the potential to be an essential strategy. To create a robust advanced traceability system, many maritime systems must continue the data learning solution approach, and our proposed AI-enhanced maritime maintenance will be considered as a reference guide.

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