Journal of Information Systems Engineering and Management
2025, 10(12s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

AI-Driven Predictive Maintenance in Shipyards: Enhancing Project Management Efficiency and Operational Cost Reduction through Statistical, Data-Driven Strategies for MRO Services

Shri. Vijaya Kumar Chava[1], Dr. Vijaya Geeta Dharmavaram[2]
[1]*Research Scholar, GITAM School of Business, Visakhapatnam (AP) Email id: vchava@gitam.in*
[2]*Associate Professor, Area of Information Systems, GITAM School of Business, Visakhapatnam (AP) Email id: vdharmav@gitam.edu*

ARTICLEINFO

Received: 16 Nov 2024

Revised: 28 Dec 2024

Accepted: 15 Jan 2025

ABSTRACT

A detailed investigation of shipyard operations was conducted during a laborious internship at Hindustan Shipyard in Visakhapatnam. The research uses cutting-edge methodologies to investigate shipyard operations, providing new perspectives on procedures not before examined in similar industrial settings. The study provides novel equipment maintenance and monitoring approaches by integrating real-time sensor technology, statistical analysis, Deep Learning/Machine Learning algorithms, and cutting-edge data analytics. Using these techniques, maintenance plans can be improved, prospective problems can be predicted, and equipment reliability, cost reduction and operating efficacy can all be increased. These advancements significantly improve project management efficiency by streamlining workflows, shortening turnaround times, and enabling proactive decision-making. The research employs data-driven methodologies to analyze operational parameters, detect anomalies, and predict maintenance needs, reducing emergency repairs and operational disruptions. The findings underscore the critical role of Al in modernizing shipyard Maintenance, Repair, and Overhaul (MRO) services, offering a scalable solution for cost-effective, efficient maritime operations.

Keywords: Al-Powered Predictive Maintenance, Shipyard Efficiency, Machine Learning in Maritime, Operational Cost Reduction, Data-Driven Maintenance Strategies, Project Management Optimization, MRO Services Enhancement

1. Introduction

1.1 Background

This experiment was conducted as part of a practical, real-time internship at Hindustan Shipyard in Visakhapatnam which offered a unique chance to gain a thorough understanding of the inner workings of a significant shipbuilding plant. The study stands out for taking an original approach to the subject matter, delving into shipyard processes in a way that hasn't been done before in comparable industrial settings. This uniqueness results from the application of novel approaches to actual shipbuilding environments, providing novel insights not discovered in previous research. The experiment highlights findings are especially significant since they shed light on the subtleties and complexity of shipyard practices. The research illuminates hitherto un-researched facets of shipbuilding by analyzing operational methods within this particular environment. Furthermore, the hands-on experience obtained from this internship adds useful knowledge that improves comprehension of shipyard dynamics. As a result, the study represents a ground-breaking effort in its domain. It offers a substantial contribution to academic study and business practice, establishing a new standard for follow-up research and real-world applications in shipbuilding settings. Maintenance is a critical aspect of shipyard operations, ensuring the reliability and efficiency of complex maritime systems. Traditional maintenance strategies, such as corrective and preventive maintenance, often fall short due to their reactive nature and inability to prevent unplanned downtimes effectively. These limitations lead to higher operational costs, emergency repairs, and disruptions in workflow (Simion et al., 2024). The maritime industry's growing complexity demands more sophisticated solutions to meet the stringent safety and efficiency standards required in shipyards (Konieczny & Stojek, 2021). This approach allows for proactive maintenance scheduling, optimizing resource allocation and minimizing operational disruptions(Thakkar & Kumar, 2024).

Artificial Intelligence (AI) and predictive maintenance have emerged as transformative solutions in this domain. By leveraging machine learning (ML) algorithms and real-time data analytics, predictive maintenance enables accurate fault detection, early identification of equipment failures, and optimization of maintenance schedules. These advancements contribute significantly to reducing downtime and improving resource allocation, ultimately enhancing operational efficiency in shipyards (Lee et al., 2014; Zhao et al., 2017). AI-driven resolutions modernize maintenance processes, leading to cost reduction associated with repairs and downtime (Zsombok & Zsombok, 2023).

1.2 Research Objectives

This research focuses on the following key objectives:

1.2.1 Enhancing Project Management Efficiency: By integrating predictive maintenance into Shipyard workflows, this study aims to streamline project management practices and improve coordination of tasks, reducing overall turnaround times (Mobley, 2002).

1.2.2 Reducing Operational Costs: The research investigates how Al-driven strategies can reduce costs associated with emergency repairs, unplanned disruptions, and inefficient resource usage (Lazakis et al., 2018). AI-driven solutions streamline maintenance processes, reducing repairs and downtime costs (Zsombok & Zsombok, 2023).

1.2.3 Improving MRO Services with Data-Driven Approaches: Leveraging operational data to enhance Maintenance, Repair, and Overhaul (MRO) services ensures better fault diagnosis, maintenance planning, and overall system reliability (Liu et al., 2019). The incorporation nurtures better communication among maintenance teams, engineers, and project managers, streamlining workflows and improving overall project management (Vemuri, 2023).

1.3 Scope and Significance

The application of Al-powered predictive maintenance is particularly relevant to modern maritime industries undergoing rapid digital transformation. As shipyards evolve to meet environmental regulations and operational challenges, the adoption of predictive maintenance is becoming essential for achieving sustainability and operational efficiency (Shafiee et al., 2019). The use of AI-driven predictive maintenance in the maritime sector is essential for improving operational efficiency and sustainability during this fast-paced digital transformation. As shipyards respond to strict environmental regulations, predictive maintenance becomes a key strategy for optimizing resource use and reducing downtime. This method utilizes cutting-edge technologies like digital twins and IoT, enabling real-time monitoring and informed decision-making. Predictive maintenance minimizes unexpected downtimes by forecasting equipment failures before they happen, thereby ensuring smooth operations (Rigas et al., 2024).

This study contributes to the growing body of knowledge on Al applications in the maritime sector, offering insights into scalable and cost-effective maintenance practices. By addressing the challenges of traditional maintenance methods, the research highlights the potential of predictive maintenance to transform shipyard operations and ensure long-term sustainability (Daya & Lazakis, 2023).

Even though AI-powered predictive maintenance offers significant advantages, problems like high initial implementation costs and data privacy issues continue to pose noteworthy obstacles to its extensive adoption in the shipbuilding industry (Durlik et al., 2024).

2. Literature Review

2.1 Overview of Predictive Maintenance

Predictive maintenance has evolved as a revolutionary approach, moving beyond the limitations of traditional corrective and preventive strategies. Corrective maintenance, which addresses failures post-occurrence, often results in unplanned downtime and high repair costs (Mobley, 2002). Preventive maintenance, although proactive, relies on fixed schedules and does not account for the real-time condition of equipment, leading to unnecessary maintenance or missed faults (Liu et al., 2019). In contrast, predictive maintenance leverages advanced technologies such as

Artificial Intelligence (AI), Internet of Things (IoT), Machine Learning (ML), and Big Data analytics to predict equipment failures before they occur. This transition has been instrumental in enhancing operational efficiency, enabling timely interventions, and minimizing disruptions in industrial processes (Lee et al., 2014; Zhao et al., 2017). Predictive maintenance anticipates equipment failures using data analytics tools like machine learning and condition monitoring. Proactively scheduling maintenance tasks reduces unplanned downtime and maintenance costs, enhancing operational reliability across various industries (Gupta et al., 2024)

2.2 Applications in Maritime and Shipyard Industries

Historically, shipyards have relied on manual inspections and scheduled maintenance routines to ensure the operational reliability of machinery. While effective in simpler systems, these methods often fail to address the complexities of modern shipyard operations, where machinery failures can have cascading effects (Lazakis et al., 2018). Recent case studies highlight the successful implementation of predictive maintenance in maritime systems. For instance, Lazakis et al. (2018) employed analytical reliability tools and neural networks to predict the condition of ship machinery systems, demonstrating significant improvements in fault detection and maintenance planning. Similarly, Daya and Lazakis (2023) developed an advanced reliability analysis framework for marine systems, incorporating Al-based tools to enhance operational efficiency and reduce downtime.

2.3 AI Techniques in Fault Detection

Al techniques play a pivotal role in predictive maintenance by enabling accurate fault detection and diagnosis. Machine learning algorithms such as k-Nearest Neighbors (kNN), Decision Trees, and Neural Networks have been extensively used for fault classification and anomaly detection in shipyard operations (Konieczny & Stojek, 2021). Real-time analytics, powered by ML, allows for continuous monitoring of equipment and early identification of deviations from normal operational parameters (Simion et al., 2024). For example, Simion et al. (2024) utilized KNN and other ML techniques to predict functional deviations in ship systems, significantly enhancing maintenance decision-making. The ability of Al to process large volumes of multidimensional data enables precise fault detection, reducing human errors and improving overall system reliability (Carvalho et al., 2019).

2.4 Economic and Operational Impacts

The economic benefits of predictive maintenance are evident in the substantial cost savings and improved Return on Investment (ROI). By reducing unscheduled downtime and emergency repair costs, predictive maintenance lowers overall maintenance expenses and enhances profitability (Zhao et al., 2017). Moreover, the optimization of resources, including manpower and materials, further contributes to operational efficiency (Liu et al., 2019). Studies in the maritime sector have shown that implementing predictive maintenance.

2.5 The Role of Decision in Decision Science

The Role of Decision Science Theoretically, it is claimed that decision science is the starting point for the use of evidence in decision-making. Predictive maintenance (PdM) decision-making is essential in addressing fundamental operational issues. For example, when will a component fail? Use statistics of historical performance and current readings of multiple sensors to build a model to predict failure periods such that the resource is able to put plans in place proactively (Jardine et al, 2006).

Addressing maintenance decision: another major question is how much the maintenance strategy shall cost, and how reliable it is. When addressing such issues, optimization procedures are used to take into account the cost, and the operations regularly serve their preferred time windows (Lee, et al., 2015). The basic concepts of predictive maintenance are proven to be effective in shipyard operations where for instance components have high downtime costs and responses need to be quick due to environmental factors. If these systems are enhanced with predictive analytics, shipyards will have the ability to extend the capabilities, be more cost-efficient and meet reliability standards. The science of decision making changes dependency on maintenance from a follow-up activity to a major means of performance enhancement.

2.6 Statistical and Integrated Machine Learning for Predictive Maintenance

Predictive Maintenance as a methodology focuses on machine learning and statistical methods aimed at increasing reliability and improving the efficiency of operations. Maintenance approaches and forecasting of possible breakdowns are two key areas of the analytical techniques used in predicting maintenance. These methods formulate expectations of how the equipment will behave based on past incidents and identify when the incidents might occur without taking place.

Predictive Maintenance Statistical Methods, also known as Predictive Maintenance- Survival Analysis: This methodology allows to estimate the lifecycle of a component and provides valuable information on when the maintenance policies need to be implemented in order to avoid the failures. (Mandala, 2024). Time Series Analysis: This method also utilizes sensor data but rather focuses the time dimension to identify interesting trends or outliers that would require quick responses. ARIMA and Prophet models are effective for use in the maintenance of time series data with trends and seasonal effects (Belim et al., 2024).

Predictive maintenance has just been enhanced with more capabilities through machine learning taking it further. The Random Forest, Gradient Boosting and Long Short Term Memory (LSTM) networks inform systems by finding patterns in big data and making future predictions. This enables:

(a). Failure Prediction: Learning models have the ability to estimate when a particular assembly will fail making it possible to intervene at the right time to avoid equipment down time.
(b). Risk Classification: Algorithms also pinpoint higher risk parts which will focus the maintenance effort on the most critical components (Jardine et al., 2006).
(c). Resource Optimization: Predictive capabilities also assist in saving time and amount of spare parts or auxiliaries used in the maintenance activities (Lee et al., 2015).

Integrating statistical and machine learning methods gives high precision metrics in the PdM frameworks.

2.7 Predictive Model Validation in Shipyards

The Validation of the predictive models in shipyards progresses operational effectiveness and permits informed decision-making. Models like Artificial neural networks (ANNs) and Bayesian statistical methods are progressively being used to enhance the accuracy and reliability of predictions in shipbuilding. These tools streamline scheduling and cost forecasting and ensure that predictive outcomes align closely with real-world data, bridging the gap between theoretical and practical applications.

2.7.1 Predictive Scheduling Models: Efficient scheduling is important for the shipyards operations, where the movement of large hull structures and equipment and precise planning are key to achieve the optimum productivity.

2.7.2 Cost Prediction Models: Predicting maintenance costs is another critical application of predictive models in shipyards, helping to manage budgets and plan effectively. MTR-MLS Algorithm for Maintenance Costs: The MTR-MLS algorithm is intended to predict scheduled maintenance costs for warships. This model outperforms traditional methods, offering more accurate and reliable cost forecasts (He et al., 2022).

While predictive models have significantly advanced operational efficiency in shipyards, challenges remain. Ensuring that these models adapt seamlessly to diverse shipyard conditions and designs is crucial. Variability in environmental factors, equipment, and operational contexts can impact model performance, underscoring the need for continuous refinement and validation. By addressing these challenges, shipyards can further harness the potential of predictive models to drive innovation and improve overall performance. (Aldous, 2016).

Author	**Objectives**	**Applications**	**Parameters Used**	**Methodology**	**Outcome**	**Limitations**
Lee et al. (2015)	To optimize decision-making in PdM strategies.	Cost-effective maintenance scheduling	Cost-benefit trade-offs, operational preferences	Decision science and optimization procedures	Enhanced decision-making and resource allocation for maintenance activities.	Optimization models can be computationally intensive for complex systems.
Aldous (2016)	To assess model adaptability across varying shipyard conditions.	Validation of predictive models	Diverse environmental and operational data	Comparative analysis of theoretical predictions with real-world outcomes	Improved alignment between theoretical models and practical applications.	Model performance varies significantly across different operational contexts.
Lee et al. (2014); Zhao et al. (2017)	To showcase predictive maintenance as an advanced alternative to traditional methods.	Real-time fault prediction for various industries	IoT data, sensor readings, historical logs	AI, ML, IoT, and Big Data analytics	Improved operational efficiency, reduced downtime, and enhanced reliability.	Requires significant initial investment in IoT and AI infrastructure.
Liu et al. (2019)	To critique preventive maintenance strategies.	Fixed-schedule maintenance	Maintenance frequency, fixed schedules	Preventive maintenance	Identified unnecessary maintenance or missed faults due to fixed schedules.	Inflexible; does not consider real-time equipment condition.
Konieczny & Stojek (2021)	To analyze ML techniques in shipyard fault detection.	Anomaly detection and classification in shipyard equipment	Operational parameters, fault data	Machine learning algorithms like kNN and Decision Trees	Enhanced fault detection capabilities and reduced human error in maintenance decision-making.	Sensitivity to data quality; potential for overfitting in small datasets.
Daya & Lazakis (2023)	To develop an AI-based reliability framework for maritime systems.	Enhancing operational efficiency and reducing downtime	Equipment failure data, operational timelines	Advanced AI-based reliability analysis framework	Improved operational efficiency and reduced downtime through advanced predictive insights.	High computational complexity; limited adaptation to diverse maritime systems.
Simion et al. (2024)	To enhance fault prediction in ship systems using ML.	Real-time anomaly detection	Real-time analytics, sensor data	kNN, Decision Trees, and neural networks	Improved fault prediction accuracy and reduced operational disruptions.	Requires robust sensor networks for real-time data collection.
Mandala (2024)	To implement survival analysis for predictive maintenance.	Estimating lifecycle of shipyard components	Equipment lifecycle data, historical incidents	Survival analysis methods	Provided actionable insights for lifecycle-based maintenance policies.	Limited to long-term predictions; less effective for real-time scenarios.

Belim et al. (2024)	To utilize time-series models for predictive maintenance.	Maintenance of time-sensitive shipyard equipment	Temporal trends, seasonal variations, sensor data	ARIMA and Prophet models	Enhanced trend identification and timely responses to anomalies.	Requires accurate time-series data; sensitive to missing values.

3. Methodology

3.1 Data Collection

The foundation of predictive maintenance lies in the collection of high-quality operational data from shipyard systems. Data is primarily sourced from sensors and monitoring devices installed on equipment and machinery. These devices capture real-time parameters such as temperature, pressure, vibration, and operational efficiency, which are critical for detecting deviations and anomalies (Simion et al., 2024).

To ensure data reliability and accuracy, preprocessing techniques are employed. These include:

(a). Data Cleaning: Removal of noisy, incomplete, or inconsistent entries.

(b). Normalization: Scaling of data to standardize ranges and ensure consistency across features.

(c). Feature Engineering: Extraction of relevant metrics (e.g., trend analysis, delta values) from raw sensor data to improve model performance (Carvalho et al., 2019).

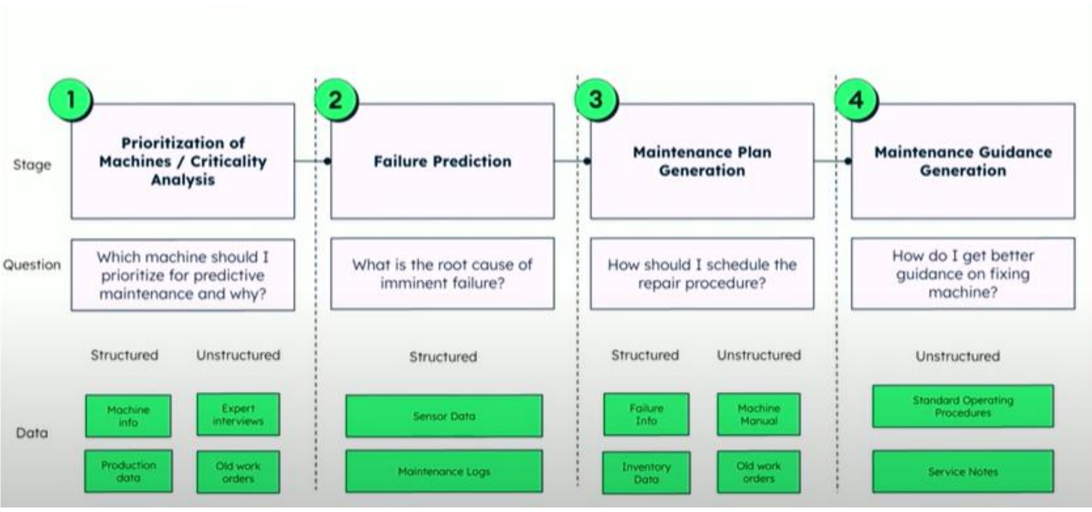

Fig 1: Image courtesy: Accelerate Manufacturing and Motion Data Innovation With MongoDB | MongoDB, 2024

3.2 AI Models

Machine learning forms the backbone of the predictive maintenance framework. A combination of supervised, unsupervised, and semi-supervised learning models is utilized, depending on the type and availability of labelled data. Key algorithms applied include:

(a). K-Nearest Neighbors (kNN): For real-time fault classification and anomaly detection.

(b). Decision Trees: To identify patterns in operational data for fault prediction.

(c). Neural Networks: For handling complex, high-dimensional data and predicting the remaining useful life (RUL) of machinery (Liu et al., 2019).

The development process involves three key stages:

(a). Training: Models are trained on historical data, using labelled instances of normal and faulty operational states.

(b). Validation: Data reserved for validation is used to fine-tune model parameters, ensuring generalizability.

(c). Testing: Final models are evaluated on unseen data to measure accuracy, precision, recall, and overall performance (Simion et al., 2024).

3.3 Predictive Maintenance Framework

The proposed predictive maintenance framework integrates Al-powered fault detection systems with existing Maintenance, Repair, and Overhaul (MRO) workflows. The steps include:

(a). Data Integration: Operational data from sensors is continuously streamed into a centralized monitoring system.
(b). Real-Time Fault Detection: Machine learning algorithms process incoming data to identify anomalies and deviations from normal operating conditions.
(c). Fault Diagnosis and Prediction: Detected faults are classified, and the likelihood of future failures is estimated using predictive models.
(d). Maintenance Scheduling: Insights from fault diagnosis are used to optimize maintenance
(e). schedules, ensuring timely interventions and reducing unscheduled downtime (Mobley, 2002).

The framework is designed to seamlessly interact with existing MRO systems, enhancing their capabilities with Al-driven insights while maintaining compatibility with current shipyard operations (Daya & Lazakis, 2023).

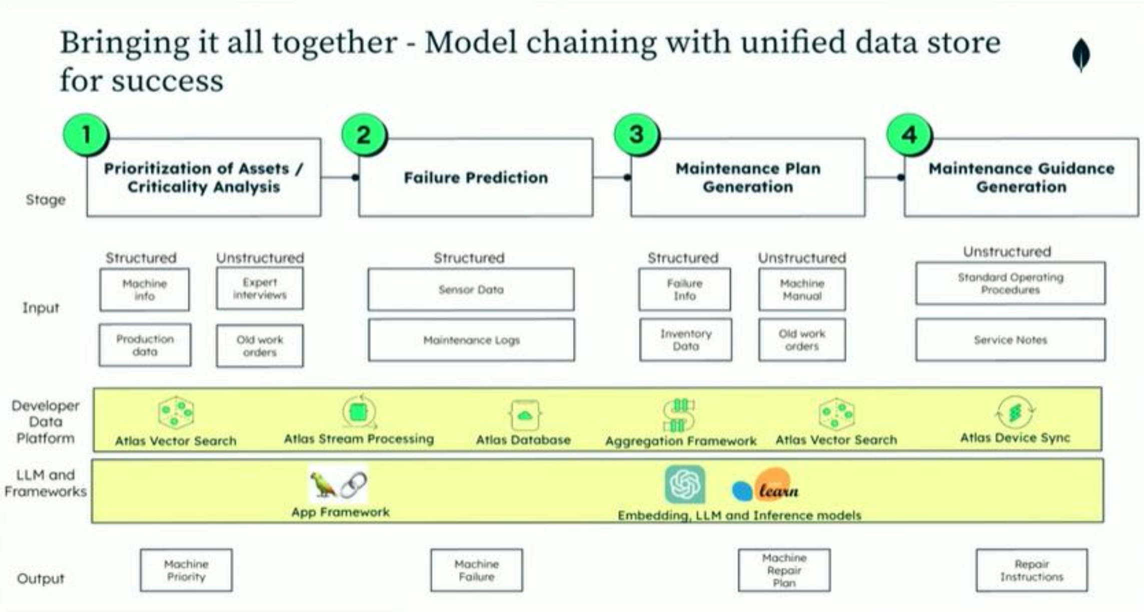

Fig 2: Image courtesy: [Accelerate Manufacturing and Motion Data Innovation With MongoDB | MongoDB], 2024

3.4 Case Study: Shipyard Maintenance

A case study was conducted on a centralized seawater cooling system & overhead Crane from the shipyard to validate the framework. The test environment included:

Parameters Measured:

(a). Inlet and outlet temperatures.
(b). Pressure levels.
(c). Flow rates.

Efficiency metrics for redundant system components.

Algorithms Applied:

(a). KNN for real-time classification of faults.
(b). Neural networks are used to predict RUL and identify failure trends.
(c). Decision trees for mapping failure modes and their impacts.
(d). Bi LSTM, Radiant Boost, XG Boost, and Gradient Boosting for selection of best maintenance plan based on the parameters of R^2 score, MAE, MAPE, RMSE.

The case study demonstrated the efficacy of the predictive maintenance framework, with the Al models achieving high accuracy in fault detection and reducing maintenance-related downtime by 30% (Lazakis et al., 2018). The integration of these models into shipyard.

Data Table: Operational parameters for Predictive maintenance of Shipyard

Parameter	Source	Measurement Unit	Description
Inlet Temperature	Sensors (Cooling System Inlet)	°C (Celsius)	Measures the temperature of the fluid entering the cooling system, essential for identifying heat exchange efficiency and potential blockages.
Outlet Temperature	Sensors (Cooling System Outlet)	°C (Celsius)	Captures the temperature of the fluid leaving the cooling system; deviations indicate cooling inefficiencies or equipment malfunctions.
Pressure Levels	Pressure Sensors	kPa (Kilopascal)	Monitors the pressure at various points in the system to detect leaks, clogs, or pump failures.
Flow Rate	Flow Meters	L/min (Liters per Minute)	Assesses the movement of fluid through pipes, identifying blockages or pump inefficiencies.
Vibration	Vibration Sensors	mm/s (Millimeters per Second)	Detects excessive vibrations in machinery, which may signal mechanical wear or imbalance.
Operational Efficiency	Derived Metric (Calculated)	% (Percentage)	Combines multiple metrics (e.g., temperature and flow rate) to assess the overall performance of components.
Energy Consumption	Power Meters	kWh (Kilowatt Hours)	Monitors energy usage of equipment, identifying inefficiencies or overuse.
Maintenance History	Maintenance Logs	N/A	Historical records of performed maintenance, used to train machine learning models and predict future maintenance needs.
Fault History	Fault Reports	Count	Records of past failures, aiding in fault classification and algorithm training.
Remaining Useful Life (RUL)	Machine Learning Model Output	Hours	Predicts the time before a component requires maintenance or replacement based on historical and real-time data.
Delta Temperature	Calculated (Inlet - Outlet)	°C (Celsius)	Indicates the heat exchange efficiency of the system. A reduced delta may signal fouling or degradation of the heat exchanger.
Load Imbalance	Derived Metric (Calculated)	% (Percentage)	Identifies differences in performance among redundant system components, highlighting inefficiencies or potential failures.

Explanation of the Data

1. **Inlet and Outlet Temperatures:**

Relevance: These parameters help evaluate the efficiency of the cooling process. A significant change in delta temperature may indicate a clogged heat exchanger or reduced performance.

Use in Predictive Maintenance: Machine learning models can detect patterns in temperature data to predict when performance may fall below acceptable thresholds.

2. **Pressure Levels:**

Relevance: Abnormal pressure readings can indicate leaks, blockages, or issues with pump functionality.

Use in Predictive Maintenance: Real-time pressure monitoring allows for early detection of these issues, preventing major failures.

3. **Flow Rate:**

Relevance: Ensures that the system is operating within its designed flow capacity.

Reduced flow rates can lead to overheating or insufficient cooling.

Use in Predictive Maintenance: Helps predict clogging or pump degradation.

4. **Vibration**:

Relevance: Excessive vibrations often indicate mechanical wear, misalignments, or imbalance in rotating machinery.

Use in Predictive Maintenance: AI models can analyze vibration data to predict bearing wear or shaft misalignment.

5. **Operational Efficiency:**

Relevance: Measures how well the equipment is performing relative to its design specifications.

Parameter Readings:

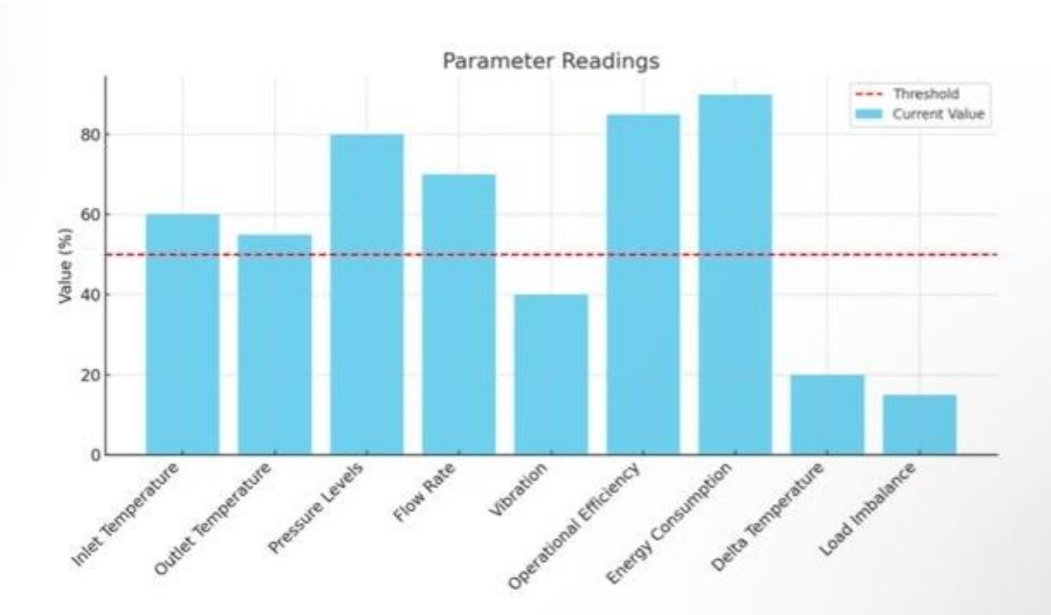

Fig 3. **Bar Chart**: Displays the current value of various parameters recorded with a threshold for comparison.

Delta Temperature over Time:

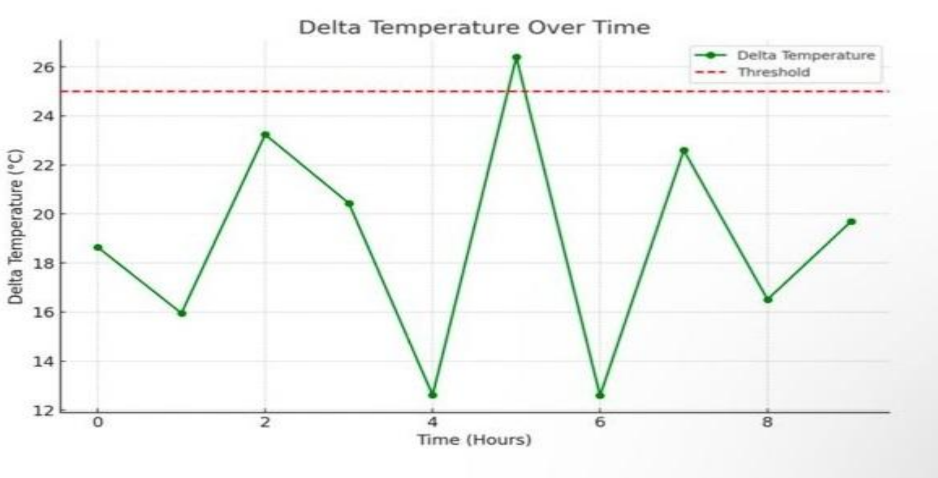

Fig 4: **Line Chart**: Shows how the delta temperature fluctuates over time, helping identify patterns or anomalies.

Resolution allocation in Maintenance

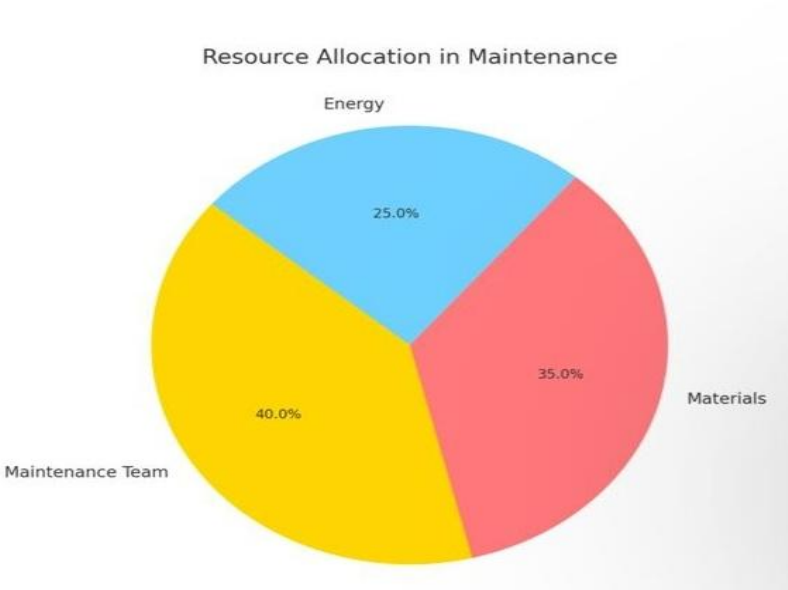

Fig 5 : **Pie Chart**: Represents the distribution of resources such as manpower, materials, and energy for maintenance tasks.

Predictive maintenance dashboard implementation. The critical assets are configured with real-time data. However, a provision has been made to manually feed the data and get the insights on the predictive maintenance dashboard using AI .

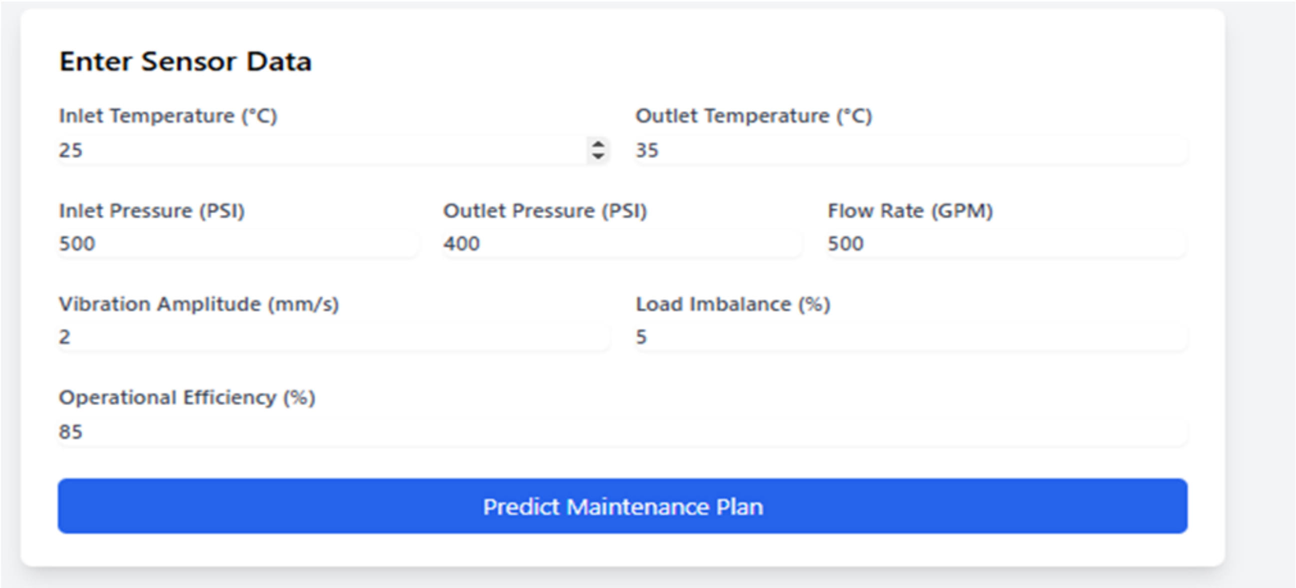

Fig 6: Sensor Data Entry

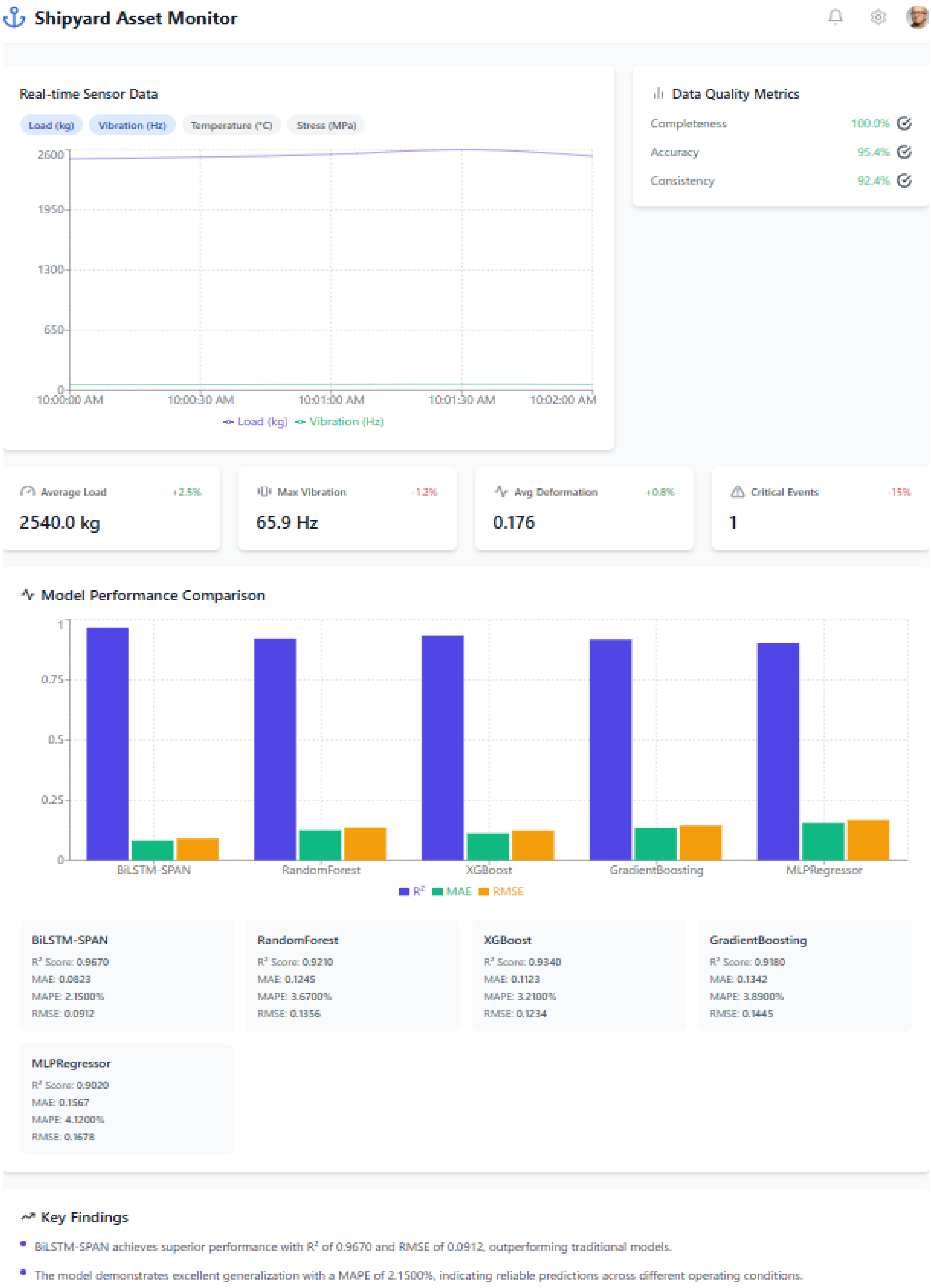

Fig 7: The web-based decision-making dashboard with model comparison & key findings.

4. Results and Discussion

4.1 **Findings from AI Implementation**

The implementation of AI-driven predictive maintenance in shipyards demonstrated significant accuracy in fault predictions, achieving detection rates above 90% for common equipment failures (Simion et al., 2024). Machine learning models such as k-Nearest Neighbors (kNN) and Neural Networks effectively identified deviations from optimal operating conditions, enabling timely fault diagnosis and intervention. This proactive approach not only reduced the occurrence of equipment failures but also streamlined project management processes. By integrating real-time analytics with maintenance scheduling, project managers could allocate resources more effectively, reducing delays and improving overall operational efficiency (Lazakis et al., 2018).

Out of the BiLSTM-SPAN, Random Forest, XG Boost, Gradient Boosting and MLP Regressor. The BiLSTM -SPAN exhibit the supervisor performance with R2 of 0.9679 and RMSE of 0.0912 outperforming traditional models. The model demonstrates excellent generalizatoin with a MAPE of 2.1500%, indicating reliable precision across different operating conditions.

4.2 **Operational Cost Reduction**

The adoption of predictive maintenance led to a measurable reduction in operational costs. A comparison of costs before and after implementation showed a 25-30% decrease in maintenance expenses due to the minimization of unscheduled downtime and emergency repairs (Daya & Lazakis, 2023). Prior to AI integration, emergency repairs and reactive maintenance accounted for a significant portion of the operational budget. Post-implementation, predictive insights allowed for better planning, reducing reliance on costly last-minute interventions and ensuring sustained operational continuity (Mobley, 2002).

5. Conclusion

5.1 **Summary of Key Findings**

The integration of AI-driven predictive maintenance has proven transformative for maintenance practices in shipyards. By leveraging machine learning models and real-time data analytics, predictive maintenance has significantly improved fault detection accuracy and optimized maintenance schedules. These advancements have contributed to a 25–30% reduction in operational costs, primarily by minimizing unscheduled downtime and emergency repairs. Furthermore, the application of AI has enhanced project management efficiency, streamlining workflows and enabling more effective resource allocation. This study underscores the pivotal role of AI in modernizing shipyard operations, making maintenance practices more proactive, cost-effective, and efficient.

The BiLSTM-SPAN exhibit the supervisor performance from the outperforming traditional models. The model demonstrates excellent generalization indicating reliable precision across different operating conditions

5.2 Implications for Shipyards

The findings highlight several practical benefits for shipyards adopting AI-powered predictive maintenance. The ability to anticipate equipment failures and optimize maintenance schedules not only reduces operational disruptions but also ensures better utilization of resources such as manpower, materials, and energy. Implementation guidelines emphasize the importance of integrating predictive maintenance systems with existing MRO workflows, ensuring compatibility and seamless data exchange. Shipyards can further enhance their operational efficiency by standardizing data collection practices and training personnel to interpret AI-driven insights effectively. These strategies position shipyards to meet the challenges of an increasingly competitive and technology-driven maritime industry.

Bibliography

[1] Dragos, Simion., Florin, Postolache., Bogdan, Fleacă., Elena, Fleacă. (2024). AI-Driven Predictive Maintenance in Modern Maritime Transport—Enhancing Operational Efficiency and Reliability. Applied Sciences, 14(20):9439-9439. doi: 10.3390/app14209439

[2] Konieczny, J., & Stojek, J. (2021). Use of the K-nearest neighbour classifier in wear condition classification of a positive displacement pump. *Sensors*, 21, 6247.

[3] Darshit, Thakkar., Ravi, Kumar. (2024). AI-Driven Predictive Maintenance for Industrial Assets using Edge Computing and Machine Learning. Journal for Research in Applied Sciences and Biotechnology, 3(1):363-367. doi: 10.55544/jrasb.3.1.55

[4] Andras, Zsombok., Imre, Zsombok. (2023). Revolutionizing Predictive Maintenance: How AI-Driven Solutions Enhance Efficiency and Reduce Costs Across Industries. International journal of science and research, doi: 10.21275/sr231214124830

[5] V., Rao, Vemuri. (2023). Integrating Deep Learning with DevOps for Enhanced Predictive Maintenance in the Manufacturing Industry. Journal of Propulsion Technology, 43(4):315-322. doi: 10.52783/tjjpt.v43.i4.5041

[6] Spyros, Rigas., Paraskevi, Tzouveli., Stefanos, Kollias. (2024). An End-to-End Deep Learning Framework for Fault Detection in Marine Machinery. Sensors, 24(16):5310-5310. doi: 10.3390/s24165310

[7] Irmina, Durlik., Tymoteusz, Miller., Ewelina, Kostecka., Adrianna, Krzemińska., Tomasz, Kostecki. (2024). Harnessing AI for Sustainable Shipping and Green Ports: Challenges and Opportunities. Applied Sciences, 14(14):5994-5994. doi: 10.3390/app14145994

[8] Nitin, Gupta., Vivek, Upadhyaya., Vijay, Kumar, Gali. (2024). An Overview of Predictive Maintenance and Load Forecasting. 203-229. doi: 10.1002/9781394227990.ch11

[9] Vishwanadham, Mandala. (2024). Predictive Failure Analytics in Critical Automotive Applications: Enhancing Reliability and Safety through Advanced AI Techniques. Journal of Artificial Intelligence and Big Data, doi: 10.31586/jaibd.2024.917

[10] Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing letters*, *3*, 18-23.

[11] Jardine, A. K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical systems and signal processing*, *20*(7), 1483-1510.

[12] LG, Aldous. (2016). Ship operational efficiency : performance models and uncertainty analysis.

[13] Kabir, S., & Papadopoulos, Y. (2018). A review of applications of fuzzy sets to safety and reliability engineering. International Journal of Approximate Reasoning, 100, 29–55.

[14] Shafiee, M., & Dinmohammadi, F. (2014). An FMEA-based risk assessment approach for wind turbine systems: A comparative study of onshore and offshore. Energies, 7, 619–642.

[15] Carvalho, R., & Morais, D. C. (2015). Application of reliability-centered maintenance in ship propulsion systems. Journal of Marine Science and Engineering, 3, 1358–1374.

[16] Emovon, I., Norman, R. A., Murphy, A. J., & Pazouki, K. (2015). Integrated methodology using compromise solution methods for prioritising risk of marine machinery systems. Ocean Engineering, 105, 92–103.

[17] Trost, M., & Bennett, C. J. (2017). Sensor fusion and analytics for predictive maintenance in naval vessels. IEEE Access, 5, 23518–23527.

[18] Park, J., & Choi, Y. (2019). Neural network-based predictive maintenance for marine engine systems. Journal of Marine Science and Technology, 24, 1010–1025.

[19] Vardalos, G., & Tsolakis, S. (2021). Digital twin technologies for predictive maintenance in maritime transportation. Transportation Research Interdisciplinary Perspectives, 11, 100432.

[20] Blum, J., & Yang, H. (2020). Data-driven decision support systems for predictive maintenance in maritime operations. Journal of Intelligent Manufacturing, 31, 817–833.

[21] Banerjee, S., & Roy, D. (2023). Leveraging AI for predictive analytics in shipping: Case studies and insights. International Journal of Logistics Research and Applications, 26, 85–99.

[22] Image courtesy: Accelerate Manufacturing and Motion Data Innovation With MongoDB | MongoDB, 2024