AI AND IoT FOR SMART TERMINALS: PREDICTIVE MAINTENANCE IN THE ERA OF DIGITALISED LOGISTICS CORRIDORS

Mr. Alessandro BERUTTI

Chief Technological Officer TMT Terminal Alexandria, Egypt, aberutti@tmterminal.com

Keywords: Predictive maintenance, Artificial Intelligence, Machine Learning, IoT, Smart terminals, Reliability, Digital logistics corridors.

ABSTRACT

The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) is transforming predictive maintenance in container terminals by enabling improved equipment reliability, safety, and sustainability. This paper presents a pilot-scale engineering validation conducted at Trans Misr Terminal (TMT), Alexandria, aimed at assessing the technical feasibility and methodological soundness of an AI- and IoT-based predictive maintenance framework under real operational conditions. The study was intentionally conducted on a single container-handling crane as a temporary pilot prior to full-scale deployment. Real-time IoT sensor data were integrated with vibration monitoring, periodic thermographic inspections, and oil-analysis diagnostics within a cloud-based analytics platform. Ensemble machine-learning techniques, including Random Forest and Quantile Random Forest models, were applied to support early degradation detection and uncertainty-aware maintenance planning. The pilot results indicate improved maintenance responsiveness and positive trends in reliability-related performance indicators such as Mean Moves Between Failures and Mean Time to Repair. While the findings are not statistically generalizable due to the limited scope, they confirm the engineering feasibility of AI-assisted predictive maintenance as a foundation for future terminal-wide implementation and smart, sustainable port operations.

1. INTRODUCTION

The digital transformation of the maritime industry is increasingly positioning ports as critical hubs of technological innovation in response to rising operational complexity, performance requirements, and sustainability targets. In this context, the convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) is enabling asset-management practices to evolve from traditional schedule-based maintenance toward intelligent, data-driven approaches. Continuous condition monitoring combined with advanced analytics now supports near real-time decision-making and improved lifecycle management of port equipment (Shaheen and Nemeth [7]; Okanminiwei and Oke [8]).

Predictive maintenance represents a key enabler of this transformation. By integrating machine-learning algorithms with IoT sensor networks, container terminals can identify early degradation, anticipate failures, and proactively plan maintenance interventions.

Compared with conventional preventive strategies, predictive maintenance supports improved equipment reliability, operational safety, and energy efficiency, capabilities that are essential for digitalized logistics corridors and resilient port operations (Breiman [1]; Zonta et al. [3]; Journal of Marine Science and Engineering [5]; Alcaraz and Zeadally [6]).

Recent industry trends reflect this shift. As illustrated in Figure 1, global investment in predictive maintenance within port and industrial environments has increased steadily in recent years, indicating a broader transition toward smart, data-driven infrastructure and cyber-physical systems (Varalakshmi and Kumar [9]; Belmoukari, Audy, and Forget [10]).

It is important to emphasize that the present work does not represent a full-scale industrial deployment, but rather a controlled pilot validation conducted within the Trans Misr Terminal (TMT) fleet. The system was intentionally implemented on a single container-handling crane and operated as a temporary test platform to address key engineering challenges related to data acquisition, system integration, diagnostic coherence, and AI feasibility under real operational conditions. The results are therefore positioned as an engineering proof of concept supporting informed decision-making prior to any terminal-wide rollout.

While numerous studies investigate predictive-maintenance algorithms using simulation or retrospective datasets, fewer contributions address the practical challenges of deploying AI-based diagnostics in live port operations characterized by heterogeneous equipment, partial digitalization, and evolving instrumentation maturity. This study addresses this gap by focusing on an engineering-driven pilot implementation rather than algorithm benchmarking, with particular emphasis on system integration, data coherence, and maintenance decision support under real terminal constraints.

The main contributions of this paper are as follows. First, the paper presents a pilot-scale engineering validation of an AI- and IoT-based predictive maintenance framework implemented under real operational conditions in a live container terminal, addressing deployment challenges often neglected in simulation-based studies. Second, it demonstrates the integration of heterogeneous diagnostic modalities, real-time IoT sensor data, vibration monitoring, thermographic inspections, and oil-analysis diagnostics, within a unified and operationally coherent maintenance framework. Third, the study introduces uncertainty-aware maintenance planning through Quantile Random Forest modeling, supporting risk-informed decision-making under variable crane duty cycles. Unlike existing works that primarily emphasize algorithmic performance, this research focuses on engineering feasibility, system integration, and operational applicability as a foundation for future terminal-wide deployment.

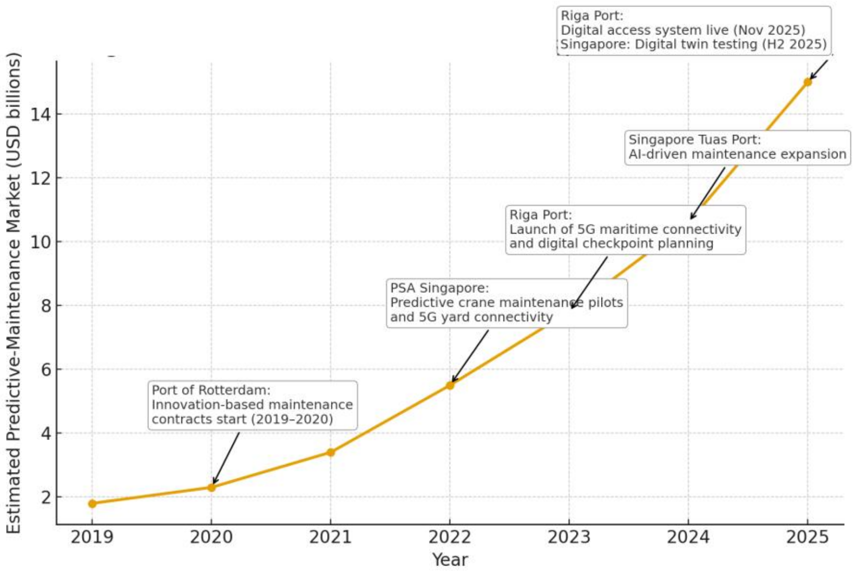

Figure 1 - Global trend in smart-port digitalisation.

Note: Illustrates global increase in predictive-maintenance projects across some maritime logistics hubs (2019-2025).

2. LITERATURE REVIEW

The development of TMT's AI- and IoT-driven predictive maintenance framework builds upon established advances in both academic research and industrial practice. Predictive-maintenance systems in industrial environments commonly rely on ensemble machine-learning techniques due to their robustness against nonlinear behavior, heterogeneous sensor inputs, and noisy operational data. Random Forests, introduced by Breiman [1], have been widely applied for reliability prediction in complex assets where data completeness may be limited. Quantile Regression Forests extend this approach by enabling probabilistic forecasting through conditional quantile estimation, supporting uncertainty-aware Remaining Useful Life prediction and maintenance planning (Meinshausen [2]).

Prior studies further demonstrate that combining multiple diagnostic modalities - such as vibration monitoring, thermographic inspection, and oil-condition analysis - enhances fault-detection robustness compared to single-sensor approaches, particularly for heavy-duty machinery (Zonta et al. [3]; Susto et al. [17]; Abidi, Mohammed, and Alkhalefah [20]).

In the port and maritime domain, predictive maintenance is increasingly associated with broader smart-port and digitalization initiatives aimed at improving operational resilience, asset availability, and sustainability. AI- and IoT-based maintenance systems are recognized as key enablers of digital transformation in container terminals (Journal of Marine Science and Engineering [5]). However, port environments impose specific constraints, including high humidity, salinity, dust exposure, and variable loading conditions, which influence monitoring strategies and algorithm performance. Chaibi and Daghrir [14] emphasize the need to adapt predictive maintenance approaches to these domain-specific characteristics. From a strategic perspective, predictive maintenance contributes to sustainable port operations by reducing unplanned downtime, emergency repairs, and material waste, thereby supporting green-port objectives (Belmoukari, Audy, and Forget [10]; Abidi, Mohammed, and Alkhalefah [22]).

As predictive-maintenance systems evolve into interconnected cyber-physical infrastructures, secure and reliable data exchange becomes a fundamental engineering requirement. Industrial control systems are exposed to specific cybersecurity vulnerabilities, necessitating secure communication, access control, and network segmentation (Alcaraz and Zeadally [6]). Scalable predictive maintenance further depends on IoT middleware capable of managing heterogeneous devices and operational data streams (Ngu et al. [11]). Optimized streaming architectures with edge-level preprocessing have been shown to reduce latency and bandwidth requirements without compromising diagnostic relevance (Varalakshmi and Kumar [9]). Integration with computerized maintenance management systems enables predictive insights to be translated into actionable workflows consistent with Industry 4.0 practices (Shaheen and Nemeth [7]).

Transition to Methodology

Based on the reviewed literature, this study implements a predictive-maintenance framework within the live operational environment of Trans Misr Terminal (TMT) in Alexandria, Egypt, as a pilot-scale engineering validation. The methodology integrates heterogeneous IoT sensor data with ensemble and quantile-based machine-learning models within a secure and interoperable architecture. The following sections describe the system architecture, data-acquisition strategy, and multimodal diagnostic approach employed to assess feasibility prior to terminal-wide deployment.

3. METHODOLOGY

The pilot dataset was collected over a twelve-month period (2024-2025) from a selected Ship-to-Shore (STS) crane operating under real terminal conditions. Continuous time-series data were acquired from vibration, temperature, and electrical sensors, complemented by periodic thermographic inspections and oil-analysis diagnostics. The sensor infrastructure generated several thousand time-indexed measurements over the monitoring period. Approximately twenty labelled degradation or abnormal operational events were identified for supervised learning. A total of ten engineered features were extracted per observation, including statistical vibration indicators, thermal trend deviations, electrical load parameters, and lubricant-condition metrics.

Raw sensor signals were preprocessed through edge-level filtering and aggregation to mitigate noise and irregular sampling. Vibration features were derived using statistical indicators such as root mean square values and trend variability, while thermal features were expressed as deviations from historical operating baselines. Oil-analysis parameters were normalized to account for sampling intervals and lubricant ageing. Missing or inconsistent measurements were excluded based on gateway-level validation checks, ensuring feature stability suitable for pilot-scale machine-learning modeling.

Consistent with the workflow shown in Figure 2, baseline data acquisition was conducted across the crane fleet to establish reference operating profiles, while advanced AI-based predictive analytics were piloted on a single selected STS crane for feasibility validation. The resulting dataset is inherently imbalanced, reflecting the predominance of normal operating conditions relative to degradation events, and is therefore treated as an engineering pilot dataset rather than a statistically representative population. The limited number of observed degradation events is primarily attributable to the relatively short operational life of the crane fleet (approximately 2.5 years), which is consistent with early-life asset behavior and further reinforces the exploratory and engineering-validation nature of the present study.

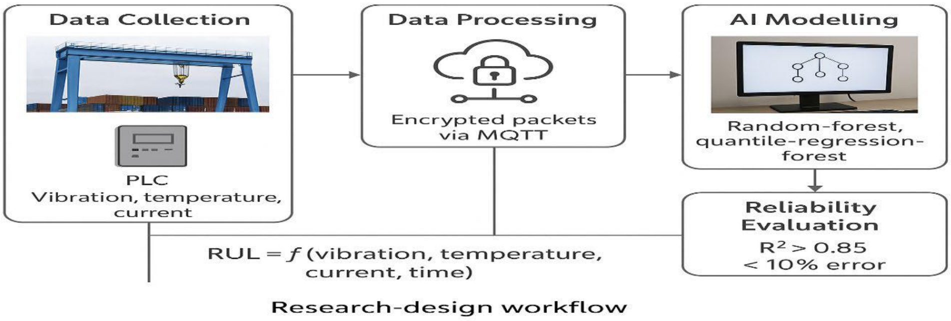

Figure 2. Research-design workflow

Note: Shows iterative process from data collection to AI modelling and reliability validation.

4. DATA ACQUISITION AND INSTRUMENTATION

4.1 E-RTG Cranes

Condition monitoring on E-RTG cranes focused on critical mechanical and electrical subsystems, including the hoist gearbox, drive motors, and major electrical components. Vibration and temperature data were acquired through conventional 4-20 mA analog transducers connected to ABB PLCs, as illustrated in Figure 3. These signals were processed within the PLC environment using threshold-based logic to trigger alarms, derating actions, or operator notifications, ensuring safe real-time operation.

Additional temperature monitoring was implemented using PTC thermistors and PT100 sensors already installed on alternators and Variable-Frequency Drive assemblies. These continuous measurements were complemented by a quarterly thermographic inspection program covering four main areas: ground-level power distribution systems, trolley and hoist drive units, electrical houses and control cabinets, and auxiliary and cabin systems. Thermal anomalies were classified as low, medium, or critical based on deviations from historical operating baselines rather than absolute temperature thresholds. This approach reflects the exploratory nature of the pilot and aligns with best practices for comparative thermographic diagnostics in industrial environments (ISO 18434-1).

The combination of continuous sensing and periodic thermographic inspection enabled the identification of mechanical wear, electrical imbalances, and early thermal anomalies, providing a robust baseline condition-monitoring layer for E-RTG cranes within the predictive-maintenance framework.

Figure 3. ERTG ABB PLC assembly on E-room including the remote I/O used for the pilot testing phase.

4.2 STS Cranes

The pilot implementation was conducted on a selected Ship-to-Shore (STS) crane to validate the feasibility of advanced predictive-maintenance analytics under real operational conditions. Vibration and temperature data were acquired using the LEAWELL Intelligent Sensing and Monitoring System (ISMS200), which comprises IEPEbased vibration-temperature sensors installed on critical rotating components, including gearboxes, motors, and bearing housings. The sensors provide broadband measurements together with embedded temperature signals, enabling the detection of early mechanical degradation during normal crane operation.

Sensor outputs were connected to LEAWELL IMS3000 intelligent monitoring stations, where high-frequency vibration signals were internally sampled for broadband analysis, while diagnostic indicators such as root mean square (RMS) values and characteristic fault metrics were computed and down-sampled to one-second resolution. Edge-level signal conditioning, filtering, buffering, and feature extraction were applied to reduce noise and data volume prior to transmission. The processed monitoring data were transmitted via Ethernet through a gateway layer to the cloud analytics environment, where machine-learning models were applied for condition assessment and trend analysis.

In parallel, conventional PLC-based measurements were retained for operational control and safety functions. This architectural separation between real-time protection logic managed by the PLCs and predictive-maintenance analytics implemented at the monitoring and cloud levels ensured safe crane operation while enabling advanced condition-monitoring capabilities within the pilot framework.

4.3 System Integration and Data Flow

The predictive-maintenance framework was implemented through hierarchical cyber-physical architecture designed to accommodate heterogeneous crane systems with different levels of instrumentation maturity. For Ship-to-Shore (STS) cranes, Siemens S7-300 PLCs acquire operational data from motion subsystems, which are managed by the Crane Management System and the Remote Crane Monitoring System prior to transmission to the cloud analytics layer through standardized application programming interfaces. In contrast, E-RTG cranes follow a hybrid digitalization approach, combining ABB PLC-based measurements for critical hoisting subsystems with analog sensors and periodic thermographic inspections for gantry and trolley mechanisms, reflecting retrofit and operational constraints.

Industrial IoT gateways (Advantech WISE-710-N600A) act as middleware components enabling protocol translation from industrial fieldbus standards (e.g., Modbus and OPC UA) to MQTT, as well as timestamp alignment and secure data forwarding to the cloud platform. The MQTT data-streaming layer was configured with Quality-of-Service level 1 (at-least-once delivery) to ensure reliable transmission of condition-monitoring data while maintaining low communication overhead. Edge-level preprocessing and buffering were implemented at the gateway and monitoring-station levels to reduce noise, optimize bandwidth usage, and preserve data continuity during temporary network interruptions. Buffered data are automatically forwarded upon reconnection, while real-time crane control and protection functions remain fully isolated within the PLC layer, ensuring operational safety. This middleware-based architecture ensures interoperable and scalable data integration across heterogeneous assets, consistent with vendor-independent smart-port frameworks described by Belmoukari, Audy, and Forget [10].

At the supervisory level, aggregated data are visualized via ThingsBoard dashboards and integrated with the IBM Maximo computerized maintenance management system to enable condition-based maintenance workflows. When AI-derived condition thresholds are exceeded, maintenance alerts are generated to support inspection scheduling and work-order creation. Cybersecurity measures follow ISO/IEC 27001 and NIST SP 800-82 Rev. 3 guidelines [13], incorporating encrypted communication channels, network segmentation, and controlled access, while maintaining acceptable latency for near real-time monitoring. Thermographic inspections, validated for early fault detection in industrial machinery by Shao et al. [15], complement vibration and oil-analysis diagnostics, completing the multimodal data flow underpinning the predictive-maintenance pilot.

4.4 Oil Analysis as Predictive Maintenance Pillar

To enhance mechanical subsystem monitoring within the pilot framework, oil-analysis diagnostics were manually introduced in 2023 using the Total Energies ANAC platform. Systematic lubricant samples collected from the hoist and trolley gearboxes of both STS and E-RTG cranes were evaluated for key oil-condition and wear-related indicators, including viscosity variation, ferromagnetic particle concentration, water contamination levels, and additive depletion.

The results provided quantitative insight into wear progression and lubricant degradation, with automatic alerts triggered when predefined abnormality thresholds were exceeded (e.g., ferromagnetic content above 150 ppm or viscosity deviation greater than 15%). These chemical diagnostics, uploaded to the Total Energies cloud platform, complemented IoT sensor data and thermographic inspections, forming a triangulated predictive-maintenance model. Oil analysis therefore constitutes a third diagnostic pillar alongside vibration monitoring and thermography, enabling earlier detection of component degradation prior to physical failure.

5. MACHINE LEARNING ALGORITHMS FOR PREDICTIVE MAINTENANCE

Machine learning forms the analytical foundation of the predictive-maintenance framework, with algorithm selection prioritizing robustness, interpretability, and scalability across heterogeneous equipment data streams. Following comparative analysis, two ensemble methods were implemented as primary predictive engines: Random Forest (RF) for Remaining Useful Life (RUL) estimation and Quantile Random Forest (QRF) for probabilistic fault detection and uncertainty quantification.

Alternative machine-learning approaches, including gradient boosting, support vector machines, and deep learning models, were considered during the system design phase. However, these techniques were not adopted due to their higher data-volume requirements, reduced interpretability, and sensitivity to irregular sampling and missing data. Ensemble tree-based methods were therefore selected as a pragmatic balance between predictive performance, robustness, and operational deploy ability in a pilot-scale industrial environment.

5.1 Random Forest (RF) Model

The Random Forest algorithm by Breiman [1], an ensemble of decision trees, was deployed for Remaining Useful Life (RUL) estimation. The final prediction is the mean of all trees:

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \tag{1}$$

where ŷ represents the predicted value (e.g., RUL or failure probability), N is the total number of trees, and Ti(x) is the prediction from the i^{th} tree for input vector x.

This ensemble-averaging mechanism improves prediction accuracy, reduces bias, and mitigates overfitting caused by noisy IoT sensor data. RF models were deployed on both crane categories and achieved stable convergence during retraining under incremental data acquisition and integration.

5.2 Quantile Random Forest (QRF) and Prediction Intervals

The Quantile Random Forest method, Meinshausen [2], was implemented to quantify uncertainty. QRF estimates the conditional distribution of the target variable, providing prediction intervals for each forecast:

$$P_L = Q(\alpha_L \mid X), P_U = Q(\alpha_U \mid X) \tag{2}$$

where Q(α | X) denotes the estimated conditional quantile function, and PL, PU correspond to the lower and upper bounds of the prediction interval for the chosen quantile levels αL and αU (e.g., 0.05 and 0.95 for a 90% interval).

The Quantile Regression Forest (QRF) framework provided prediction intervals alongside point forecasts, offering probabilistic reliability windows for failure events. This was critical for cranes with highly variable duty cycles, where mechanical stress is non-uniform. By quantifying uncertainty in Remaining Useful Life (RUL) estimates, the system enabled planners to schedule maintenance and spare-parts logistics based on operational risk thresholds, facilitating a shift from deterministic to truly risk-aware maintenance strategy, as established by Meinshausen [2].

6. TEST SYSTEM IMPLEMENTATION

The framework was implemented in three sequential phases:

6.1 Infrastructure setup - device installation and network configuration.

6.2 Platform integration - connecting IoT data streams to ThingsBoard dashboards.

6.3 Operational validation - pilot deployment and KPI monitoring.

Sensor data flows from PLCs through industrial edge gateways to a secure cloud-based dashboard, with integration to TMT's IBM MAXIMO CMMS module. This enables automatic work order generation when predefined thresholds are exceeded, realizing the vendor-agnostic interoperability principles established by Belmoukari, Audy, and Forget [10].

The dashboard (Figure 4) implements a triage system for maintenance response:

a) Green: Normal - Continue monitoring

b) Amber: Degradation detected - Schedule inspection

c) Red: Imminent failure - Immediate intervention

This color-coded logic enables rapid response prioritization while maintaining the secure data transmission protocols outlined in NIST SP 800-82 Rev. 3 [13].

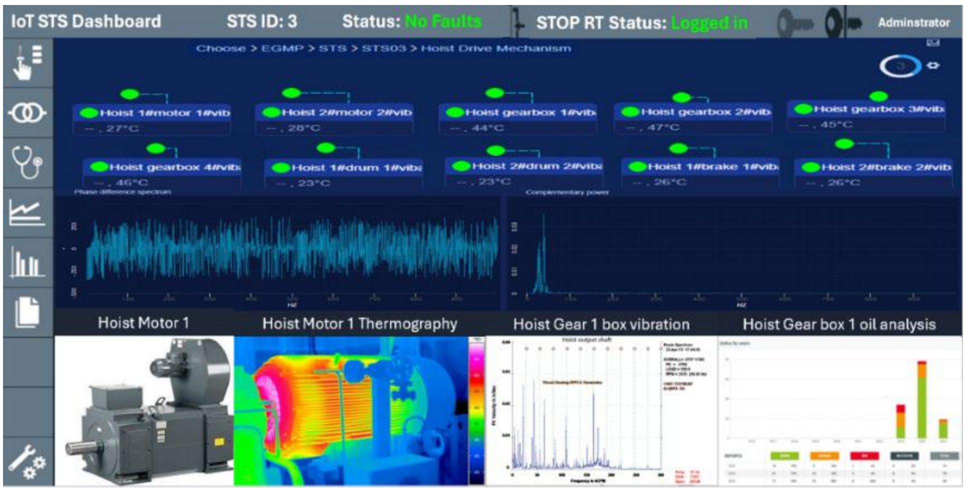

Figure 4 - IoT STS Dashboard at TMT.

Note: The page shows the real time status of hoist and detail of motor 1 of STS3.

http://dx.doi.org/10.21622/MARLOG.2026.15.1.65

7. MODEL VALIDATION AND EVALUATION

The models were validated through a two-stage procedure: statistical verification and engineering correlation with maintenance records on CMMS.

7.1 Validation Framework

Historical datasets from the Remote Crane Monitoring System (RCMS) and IBM Maximo CMMS were divided using an 80:20 training-testing ratio with five-fold cross-validation to minimize bias. Each model was assessed using three complementary performance indicators:

(1) Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

Where:

- **y_i:** actual (observed) value
- **$\hat{y}_i$:** predicted value
- **$\bar{y}$:** mean of actual values
- **n:** number of samples

This measures how well the regression model explains the variance in the data (values closer to 1 indicate a better fit).

(2) Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{4}$$

MAE expresses the average absolute deviation between predicted and actual values; lower values mean better predictive accuracy.

(3) Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{5}$$

Where y_i and $\hat{y}_i$ denote observed and predicted RUL values, respectively, and $\bar{y}$ is the sample mean. These metrics collectively evaluate model performance: R^2 quantifies explained variance, MAE measures average absolute deviation, and MAPE expresses error as a percentage of actual values. While MAPE requires cautious interpretation when actual values approach zero, it remains a standard measure for relative prediction accuracy, as documented in Scikit-learn [16].

7.2 Validation Results

The RF and QRF models consistently achieved $R^2 > 0.85$, MAE < 8%, and MAPE < 10% on test data. QRF was associated with improvements of well-calibrated prediction intervals. Cross-checking against IBM Maximo CMMS records showed a realistic correlation between predicted degradation and actual maintenance events, validating the system's practical utility.

7.3 Engineering Validation and Operational Consistency

Given the pilot scope and the limited number of degradation events, model performance and reliability improvements were evaluated through engineering validation and operational consistency, rather than formal large-sample hypothesis testing. Confidence intervals and inferential statistical analyses are therefore deferred to future terminal-wide deployment phases, where longer monitoring horizons and larger datasets will be available.

Model predictions were systematically compared with actual maintenance interventions recorded in the IBM Maximo CMMS. A clear temporal alignment was observed between predicted degradation inflection points and executed maintenance actions, supporting the practical usefulness of the AI system as a decision-support tool within the pilot context. Early anomaly detection enabled planned maintenance interventions and improved resource allocation, contributing to an indicative increase in Mean Moves Between Failures (MMBF) and a reduction of over 20% in Mean Time to Repair (MTTR).

These results demonstrate that the proposed framework delivers operationally consistent and engineering-coherent outcomes, in line with established reliability engineering principles for port equipment performance assessment, as discussed by Okanminiwei and Oke [8].

8. RESULTS AND DISCUSSION

During the 2024-2025 observation period, the pilot implementation of AI- and IoT-enabled predictive maintenance was associated with measurable improvements in operational and reliability-related performance indicators, as summarized in Table 1.

Table 1. Key Performance Indicators Before and After Implementation

KPI	Baseline (2023)	After Implementation	Improvement
STS Availability	93%	97%	4%
E-RTG Availability	90%	98%	8%
MMBF (STS)	2012	2215	10%
MMBF (E-RTG)	1885	1993	6%

To ensure comparability between baseline and pilot periods, KPI values were normalized by crane utilization rates and cumulative operating hours, accounting for workload variability and operational intensity. While the limited duration and scope of the pilot preclude statistical generalization, the observed trends are consistent with improved maintenance responsiveness and reduced unplanned downtime.

The integration of oil-analysis diagnostics proved particularly valuable for mechanical subsystems, enabling the early identification of gearbox degradation and lubricant contamination. As a result, two planned main gearbox replacements were avoided in 2025, demonstrating the effectiveness of combining real-time IoT monitoring with periodic offline lubricant diagnostics. This finding confirms the synergistic benefit of a multimodal condition-monitoring strategy over single-diagnostic approaches.

In addition, early warning alerts generated by the predictive-maintenance framework supported condition-based spare-parts planning, reducing emergency procurement events by approximately 10%. Beyond cost benefits, this improvement contributed to smoother maintenance scheduling and reduced operational disruptions. The associated reductions in corrective maintenance interventions and energy-intensive emergency repairs align with the CMA Terminals Group's decarbonization and sustainability objectives, highlighting the practical contribution of AI- and IoT-enabled predictive maintenance to smart and sustainable port operations (Alcaraz and Zeadally [6]; Varalakshmi and Kumar [9]; Belmoukari, Audy, and Forget [10]).

9. CONCLUSIONS

This study presented a pilot-scale validation of an AI and IoT enabled predictive-maintenance framework implemented at Trans Misr Terminal, demonstrating its technical feasibility and engineering coherence under real operational conditions. The integration of heterogeneous sensor data with machine-learning analytics supported improved maintenance responsiveness and indicative gains in reliability-oriented performance indicators, including reduced unplanned downtime and improved asset utilization for the tested crane. The results confirm the potential of transitioning from traditional preventive maintenance toward data-driven predictive strategies in container-terminal operations, while highlighting the importance of phased deployment and engineering validation prior to full-scale adoption. Future work will focus on extending the framework to additional Container Handling Equipment, such as reach stackers and others, as well as on expanding the dataset to support long-term performance assessment and model refinement.

10. ACKNOWLEDGEMENTS

The author acknowledges the support of the Trans Misr Terminal Engineering Department and the technical cooperation of TMT colleagues throughout this research.

11. DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES

During the preparation of this work, the author used ChatGPT for text formatting, and reference structuring according to MARLOG 15 guidelines. The author reviewed and edited all content and takes full responsibility for the final publication.

12. REFERENCES

[1] Breiman, L. 2001. "Random Forests." Machine Learning 45 (1): 5-32. https://doi.org/10.1023/A:1010933404324

[2] Meinshausen, N. 2006. "Quantile Regression Forests." Journal of Machine Learning Research 7: 983-999. https://www.jmlr.org/papers/volume7/meinshausen06a/meinshausen06a.pdf

[3] Zonta, T., C. A. da Costa, R. da Rosa Righi, M. de Lima, E. S. da Trindade, and G. P. Li. 2020. "Predictive Maintenance in the Industry 4.0: A Systematic Literature Review." Computers & Industrial Engineering 150: 106889. https://doi.org/10.1016/j.cie.2020.106889

[4] Cummins, L., A. Gal, and M. Danilevsky. 2024. "Explainable Predictive Maintenance: Current Methods and Challenges." IEEE Access. https://doi.org/10.1109/ACCESS.2024.3391130

[5] Journal of Marine Science and Engineering. 2022. "Digitalization in Maritime Transport and Seaports: Bibliometric, Content and Thematic Analysis." Journal of Marine Science and Engineering 10 (4): 486. https://doi.org/10.3390/jmse10040486

[6] Alcaraz, C., and S. Zeadally. 2015. "Critical Infrastructure Protection: Requirements and Challenges for the 21st Century." International Journal of Critical Infrastructure Protection 8: 53-66. https://www.sciencedirect.com/science/article/abs/pii/S1874548214000791

[7] Shaheen, B. W., and I. Nemeth. 2022. "Integration of Maintenance Management System Functions with Industry 4.0 Technologies and Features - A Review." Processes 10 (11): 2173. https://doi.org/10.3390/pr10112173

[8] Okanminiwei, L., and S. A. Oke. 2021. "Port Equipment Downtime Prediction and Lifetime Data Analysis: Evidence from a Case Study." Journal of Industrial Engineering and Management Systems (JIEMS) 14 (1): 8-18. https://doi.org/10.30813/jiems.v14i1.2362

[9] Varalakshmi, K., and J. Kumar. 2025. "Optimised Predictive Maintenance for Streaming Data in Industrial IoT." Scientific Reports 15 (1): 10268-10288. https://doi.org/10.1038/s41598-025-10268-8

[10] Belmoukari, B., J.-F. Audy, and P. Forget. 2023. "Smart Port: A Systematic Literature Review." European Transport Research Review 15 (1): 4. https://doi.org/10.1186/s12544-023-00581-6

[11] Ngu, A. H., M. Gutierrez, V. Metsis, S. Nepal, and Q. Z. Sheng. 2017. "IoT Middleware: A Survey on Issues and Enabling Technologies." IEEE Internet of Things Journal 4 (1): 1-20. https://doi.org/10.1109/JIOT.2016.2615180

[12] Lundberg, S. M., and S.-I. Lee. 2017. "A Unified Approach to Interpreting Model Predictions." Advances in Neural Information Processing Systems (NeurIPS). https://doi.org/10.5555/3295222.3295230

[13] National Institute of Standards and Technology (NIST). 2023. Guide to Industrial Control Systems (ICS) Security. NIST Special Publication 800-82 Rev. 3. https://doi.org/10.6028/NIST.SP.800-82r3

[14] Chaibi, M., and J. Daghrir. 2024. "Artificial Intelligence for Predictive Maintenance of Port Equipment: A Revolution in Progress." In Artificial Intelligence and Smart Port Systems, edited by Springer. https://link.springer.com/chapter/10.1007/978-3-031-67152-4_35

[15] Shao, H., M. Xia, G. Han, E. Zhang, and J. Wan. 2021. "Intelligent Fault Diagnosis of Rotor-Bearing System under Varying Working Conditions with Modified Transfer Convolutional Neural Network and Thermal Images." IEEE Transactions on Industrial Informatics 17 (8): 5341-5350. https://doi.org/10.1109/TII.2020.3005965

[16] Scikit-learn Documentation. 2025. "Regression Metrics: r2_score, mean_absolute_error, mean_absolute_percentage_error." Version 1.5. https://scikit-learn.org/stable/modules/model_evaluation.html

[17] Susto, G. A., A. Schirru, S. Pampuri, S. McLoone, and A. Beghi. 2015. "Machine Learning for Predictive Maintenance: A Multiple Classifier Approach." IEEE Transactions on Industrial Informatics 11 (3): 812-820. https://pureadmin.qub.ac.uk/ws/files/17844756/machine.pdf

[18] Aslam, S., A. Navarro, A. Aristotelous, E. G. Crevillen, A. Martinez-Romero, A. Martinez-Ceballos, A. Cassera, K. Orphanides, H. Herodotou, and M. P. Michaelides. 2025. "Machine Learning-Based Predictive Maintenance at Smart Ports Using IoT Sensor Data." Sensors 25 (13): 3923. https://www.mdpi.com/1424-8220/25/13/3923

[19] Drakaki, M., Y. L. Karnavas, I. A. Tziafettas, V. Linardos, and P. Tzionas. 2024. "Machine Learning and Deep Learning-Based Methods Toward Industry 4.0 Predictive Maintenance in Induction Motors: State of the Art Survey." Journal of Industrial Engineering and Management (JIEM). https://www.jiem.org/index.php/jiem/article/view/3597

[20] Abidi, M. H., M. K. Mohammed, and H. Alkhalefah. 2022. "Predictive Maintenance Planning for Industry 4.0 Using Machine Learning for Sustainable Manufacturing." Sustainability 14 (6): 3387. https://www.mdpi.com/2071-1050/14/6/3387