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AI-Based Lifespan Estimation and Energy Efficiency Optimization of Port Ship Unloaders Motors Under Harsh Environmental Conditions

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Original Research

Abstract:

Electric motors in port ship unloaders operate under harsh environmental conditions that accelerate degradation and increase energy consumption. This study develops a unified hybrid predictive maintenance framework that integrates an adaptive Extended Kalman Filter (EKF), a Long Short-Term Memory (LSTM) network, and Deep Reinforcement Learning (DRL). The EKF—enhanced with the adaptive Sage–Husa algorithm—serves as a dynamic state estimation and noise-mitigation module, improving the quality of multi-sensor data before learning and decision-making. The LSTM component captures nonlinear temporal degradation patterns, while the DRL agent learns optimal maintenance policies that balance reliability, operational safety, and energy efficiency.
The proposed EKF–LSTM–DRL framework was validated on real and simulated datasets from Neuero ship unloader motors at Bandar Imam Khomeini Port (Iran). Results show a 20% reduction in Mean Absolute Error (MAE) and a 15% decrease in unplanned downtime compared with baseline models such as GRU and CNN. The main contributions of this work are: (1) a clear integration of adaptive EKF-based preprocessing with deep learning and reinforcement learning for robust Remaining Useful Life (RUL) prediction under maritime uncertainty; and (2) a dual optimization of predictive accuracy and energy efficiency. A detailed workflow diagram has been added to clarify the complete process and ensure conceptual transparency.

Keywords:

Environmental stress; Maintenance planning: Remaining Useful Life (RUL); Artificial intelligence; Deep reinforcement learning; Energy saving

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1. Introduction

In industrial and maritime environments, heavy machinery-especially ship unloader motors-is continuously subjected to harsh operating conditions that accelerate degradation, increase energy consumption, and reduce system reliability. These challenges are particularly evident at Bandar Imam Khomeini Port (Iran), where high temperature, humidity, and airborne dust intensify the mechanical and electrical stresses experienced by port equipment. As a result, the reliability and service life of such motors are severely affected, leading to frequent failures and high maintenance costs. Therefore, the development of accurate Remaining Useful Life (RUL) prediction models and intelligent maintenance planning strategies is crucial to ensure sustainable and efficient port operations.

Conventional reliability and Dynamic State Estimation (DSE) techniques, such as those based on Kalman filtering, have proven valuable for estimating hidden system states and mitigating sensor noise. However, these approaches are inherently limited when dealing with highly nonlinear, non-stationary degradation processes that evolve over long operational periods. To address these limitations, this study employs the Extended Kalman Filter (EKF)-enhanced by the adaptive Sage–Husa noise estimation algorithm-not as the main predictive engine but as a data preprocessing and noise-mitigation module. The adaptive EKF dynamically

estimates measurement noise and corrects raw sensor signals, providing high-quality input features for subsequent data-driven modeling. This ensures robust data integrity before the deep learning stages of analysis.
Following this adaptive filtering, a Long Short-Term Memory (LSTM) network is used to capture complex temporal and nonlinear dependencies in the degradation trajectories of port motors. To complement the LSTM's predictive capability, Deep Reinforcement Learning (DRL)-implemented via a Deep Q-Network (DQN)-is integrated to learn optimal maintenance policies that balance reliability, downtime reduction, and energy efficiency. This synergy between EKF-based preprocessing, LSTM-based temporal learning, and DRL-based decision optimization forms a unified hybrid framework capable of operating effectively under uncertain and variable environmental conditions.
The proposed EKF–LSTM–DRL framework was validated using real and simulated datasets from Neuero ship unloader motors at Bandar Imam Khomeini Port. Comparative results against GRU and CNN baseline models demonstrate the superior accuracy and robustness of the proposed method.
Collectively, this research contributes a practical, adaptive, and data-driven solution for predictive maintenance in harsh maritime environments, offering direct benefits in cost reduction, reliability improvement, and enhanced operational efficiency in port logistics systems [1].
This study presents several novel contributions to the domain of intelligent predictive maintenance and reliability optimization for port machinery operating under harsh maritime conditions:

1. Hybrid EKF–LSTM–DRL Framework: The paper introduces a unified hybrid model that integrates the adaptive Sage–Husa–based Extended Kalman Filter (EKF) with a Long Short-Term Memory (LSTM) network and Deep Reinforcement Learning (DRL). This integration bridges the gap between dynamic state estimation and data-driven learning, providing robust Remaining Useful Life (RUL) prediction under uncertainty.

2. Adaptive Preprocessing Using EKF: Unlike traditional DSE approaches, the EKF in this study is designed as an adaptive preprocessing module that dynamically estimates and compensates measurement noise. This enhances the accuracy of sensor data and improves the quality of inputs for subsequent deep learning analysis.

3. Dual-Objective Optimization: The proposed approach jointly optimizes two essential objectives—RUL prediction accuracy and energy-efficiency improvement—enabling both reliability enhancement and sustainable operation of port machinery.

4. Validation on Real Port Data: The framework is validated using a combined real and simulated dataset collected from Neuero ship unloader motors at Bandar Imam Khomeini Port (Iran). The results demonstrate a 20% reduction in prediction error and a 15% decrease in unplanned downtime compared with conventional deep-learning models.

5. Enhanced Transparency and Reproducibility: To ensure methodological clarity, a new flowchart (figure 4) and detailed algorithmic description (Appendix 2) have been added to illustrate the complete workflow—from data acquisition and EKF-based noise filtering to LSTM-driven degradation modeling and DRL-based maintenance decision-making.

Overall, these contributions advance the current state of predictive maintenance research by integrating adaptive signal estimation, deep temporal learning, and reinforcement-based optimization into a single interpretable and generalizable framework for intelligent asset management in maritime industries.
The rest of the paper is organized as follows: section 2 reviews related work, section 3 presents the methodology and model structure, section 4 discusses experimental results and analysis, and section 5 concludes with insights and directions for future research.

1.1 Literature review

Remaining Useful Life (RUL) estimation has undergone extensive evolution over recent decades. Earlier methods primarily relied on physics-based models that required a deep understanding of the underlying degradation mechanisms [2]. While these models provided valuable insights, their practical implementation was often limited by system complexity, parameter uncertainty, and environmental variability. With the emergence of machine learning, data-driven approaches-especially those using deep learning-have outperformed traditional methods by effectively capturing nonlinear and temporal degradation behavior [3]. Advanced deep-learning architectures, such as CNN–LSTM and GRU–Attention hybrids, have demonstrated superior predictive accuracy in RUL estimation tasks [4]. The integration of Deep Reinforcement Learning (DRL) with deep-learning-based models further improves adaptability in dynamic and uncertain environments [5]. In the maritime sector, AI-driven techniques like LSTM and DRL have been successfully applied for energy optimization, vessel navigation, and equipment health monitoring [6]. However, their application in extreme environments—characterized by high dust levels, salinity, and heat—such as those found at Bandar Imam Khomeini, remains relatively unexplored [7]. The direct impact of these environmental factors on motor degradation is an important research gap that this study aims to address.
In the field of Dynamic State Estimation (DSE), Kalman-based algorithms, including the Extended Kalman Filter (EKF), are widely employed to manage uncertainties and nonlinearities in complex systems [8]. Recent works suggest incorporating adaptive noise estimation mechanisms-such as the Sage-Husa algorithm-to dynamically update measurement noise statistics and enhance real-time performance [9]. These adaptive approaches have shown high robustness against varying and uncertain noise sources, making them well-suited for real-world industrial applications.
Therefore, this study combines the strengths of three complementary approaches:

1. The temporal learning capability of LSTM,

2. The adaptive decision-making power of DRL, and
3. The enhanced noise-handling ability of the Sage–Husa–based EKF.

Together, these elements form a comprehensive predictive-maintenance framework designed for accurate RUL estimation under the severe environmental stresses encountered in maritime and port operations [10].

Figure 1. A typical Neuero ship unloader

a. Environmental factors impacting lifespan reduction and increased energy consumption

In port environments, heavy-duty machinery such as unloading and loading motors are exposed to harsh environmental conditions that significantly accelerate wear and energy consumption. The most critical environmental factors contributing to reduced equipment lifespan and increased energy usage include elevated temperature, high humidity, and airborne dust. Their effects can be summarized as follows:

b. Electrical resistance and temperature

The equation 1 is derived from Ohm's Law and linear temperature dependence of resistivity for conductors is widely used in motor design standards, including those published by IEEE and IEC. Triantafilou, Vladimir [11].

$$R_T = R_{25}[1+\alpha(T-25)] \tag{1}$$

where:
R_T and R_{25}: Electrical resistance of the conductor at temperature T (in °C) and 25 respectively.
α: Temperature coefficient of resistance ($\approx$ 0.00393/°C for copper)
T: Ambient or operating temperature in °C

c. Joule losses in motor windings

Based on the Joule Losses law as offered in equation 2; amount of power loss increases with both higher current draw and elevated temperature due to increased resistance [11]. This is one of the dominant forms of energy loss in electric motors windings.

$$P_{\text{loss}} = I^2 R_T \tag{2}$$

where:
P_{loss}: Power loss due to resistance (watts)
I: Current flowing through the motor windings (amperes)
R_T: Resistance at the operating temperature

d. Insulation life – arrhenius equation

A classical thermochemical degradation model used to estimate insulation aging under thermal stress depicted by equation 3. It's accepted by both IEEE Std 98 and IEC 60216 [12].

$$L_T = L_0 \cdot e^{-\frac{E_0}{k(T+273)}} \tag{3}$$

L_T: Expected lifetime of insulation at temperature T (in °C)
L_0: Lifetime at a reference temperature
E_0: Activation energy for thermal degradation (e.g., 0.7 – 1.1 eV for common polymers)
k: Boltzmann constant (8.617×10^{-5} eV/K)
T: Operating temperature in °C

e. Leakage current and humidity

While not an equation per se, this proportional relationship describes how relative humidity (RH) adversely affects insulation performance, especially in coastal or maritime environments IEEESTD.6511506 [13].

$$I_{\text{leak}} \propto \frac{1}{R_{\text{insulation}}} \tag{4}$$

$R_{\text{insulation}} \downarrow$ as humidity increases
I_{leak}: Leakage current through motor insulation
$R_{\text{insulation}}$: Insulation resistance, which decreases with moisture content
Corrosion Rate under Humidity and Ionic Exposure
A simplified empirical model reflects the synergistic effects of temperature, humidity, and airborne salt/dust particles common in port environments is presented by equation 5. According to ASTM B117 [14]. actual corrosion rates are often determined via accelerated aging tests like salt spray.

$$r_{\text{corrosion}} \propto RH \cdot T \cdot C_{\text{ion}} \tag{5}$$

$r_{\text{corrosion}}$: Corrosion rate of exposed metal components
RH: Relative humidity (dimensionless, as a fraction)
T: Ambient temperature (°C)
C_{ion}: Concentration of corrosive ions (e.g., Cl^-, $SO_4{}^{2-}$)
Thermal Resistance and Surface Temperature
Dust buildup increases thermal resistance by blocking airflow and insulating surfaces, which can result in dangerous overheating if not managed. Here Temperature rise (ΔT) above ambient (°C) could be explained by equation 6 [15].

$$\Delta T = P_{\text{loss}} \cdot R_{\text{th}} \tag{6}$$

where:
P_{Loss}: Power dissipated as heat (watts)
R_{th}: Thermal resistance from motor surface to ambient (°C/W)

f. Motor efficiency with increased losses

According to NEMA standard MG 1 [16]. environmental factors elevate total internal power loss , efficiency declines, leading to higher energy consumption and operating cost over time depicted by equation 7.

$$\eta = \frac{P_{\text{out}}}{P_{\text{out}} + P_{\text{loss}}} \tag{7}$$

Here:
η: Overall motor efficiency ($0 < \eta < 1$)
P_{out}: Useful mechanical output power (watts)
P_{loss}: Total internal power loss (watts), including copper, iron, and friction losses.

2. Methodology

This section describes the proposed hybrid methodology for predicting the Remaining Useful Life (RUL) of Neuero ship unloader motors operating under severe maritime environmental conditions. The framework combines three complementary components: an adaptive Extended Kalman Filter (EKF) with Sage–Husa noise estimation, a Long Short-Term Memory (LSTM) neural network, and Deep Reinforcement Learning (DRL) implemented through a Deep Q-Network (DQN).
The overall design is structured such that the EKF acts as a preprocessing module rather than a standalone Dynamic State Estimation (DSE) system. It dynamically estimates sensor noise and corrects input signals before they are used by the LSTM model. This adaptive filtering ensures that real-time degradation data remain stable and representative under varying temperature, humidity, and dust levels common in port environments. The filtered and noise-compensated data are then passed to the LSTM network, which learns long-term temporal dependencies and nonlinear degradation patterns.
Following LSTM-based RUL prediction, the DRL component continuously learns optimal maintenance actions based on the predicted health state and system performance indicators. The Deep Q-Network (DQN) is trained to minimize the Mean Absolute Error (MAE) between predicted and actual RUL values while maximizing energy efficiency and operational reliability. This adaptive decision-making process allows the agent to select the best maintenance strategy-repair, replacement, or continued operation—according to real-time operating conditions.
The workflow of the proposed EKF–LSTM–DRL hybrid framework is later illustrated in figure 4. It clearly demonstrates the data flow from sensor acquisition, EKF-based preprocessing, LSTM-driven degradation modeling, to DRL-based maintenance optimization. To maintain clarity and reproducibility, the detailed algorithmic description is provided in Appendix 2, and the pseudocode structure is presented in Appendix 3.
The dataset used for validation was collected from condition-monitoring sensors installed on Neuero ship unloader motors at Bandar Imam Khomeini Port, Iran. Data preprocessing involved normalization, smoothing, and missing-value handling to ensure consistency and model convergence stability. The hybrid model was trained and evaluated using both real and simulated data to capture a wide range of operational conditions, including noise, dust exposure, and temperature fluctuations. The model's predictive performance was assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics, confirming its robustness and accuracy under real port conditions.
Overall, this methodology represents an intelligent integration of adaptive estimation, deep learning, and reinforcement learning. It moves beyond traditional DSE methods by embedding dynamic noise estimation and policy optimization directly into the predictive maintenance process.

a. Data Collection

Data were collected from Neuero grain suction motors installed at Bandar Imam Khomeini Port, Iran, between March 1 and June 22, 2023, resulting in 2,880 hourly samples. The dataset comprises mechanical parameters (vibration, speed, and bearing temperature), electrical signals (stator winding temperature and power consumption), and relevant environmental variables (see Table 1).
Because the number of real fault events was limited, simulated failure scenarios were also generated to enrich the dataset. These artificial cases (Table 3) were designed using critical thresholds based on engineering standards and were cross-validated with historical maintenance and operational reports to ensure consistency with actual degradation patterns under the port's harsh environmental conditions [17]. This combined dataset-containing both real and simulated data-ensures that the proposed framework can learn from a wide range of operating states, improving the reliability and generalization capability of the RUL prediction model.
• Graphs of sensor characteristics (VIB1_mms, VIB2_mms, Bearing_Temp_A, Bearing_Temp_B, Winding_Temp, Speed_RPM, Power_KW) over the full 2880-hour period

Table 1. Environmental conditions at Imam Khomeini Port during data collection.

Month	Average temperature (°C)	Average humidity (%)	Dust exposure level
March 2023	28	60	High
April 2023	32	62	High
May 2023	38	65	High
June 2023	42	70	High

Table 2. Sample data with simulated RUL.

Timestamp	VIB1_mms	Winding Temp (°C)	Bearing Temp (°C)	RUL (Simulated, Hours)
2023-06-22 08:59:59	3.7	120.2	99.5	100
2023-06-22 11:59:59	5.6	126.0	106.0	73.5

Table 3. Simulated failure data for Neuero motors at Imam Khomeini Port.

Failure ID	Failure Time	VIB1mms	Bearing (°C)	Winding (°C)	Failure Cause	Environmental conditions
1	2023-04-15 14:00:00	7.5	110	130	High Vibration	Temp: 32°C, Humidity: 62%, High dust
2	2023-05-10 09:30:00	6.8	118	132	High Bearing Temp	Temp: 38°C, Humidity: 65%, High dust
3	2023-05-25 16:45:00	7.2	112	138	High Winding Temp	Temp: 38°C, Humidity: 65%, High dust
4	2023-06-05 11:20:00	7.8	116	134	High Vibration	Temp: 42°C, Humidity: 70%, High dust
5	2023-06-20 08:10:00	6.9	120	136	High Bearing Temp	Temp: 42°C, Humidity: 70%, High dust

(March 1 to June 22, 2023). The overall increasing trend in vibrations, temperatures, and power consumption, along with decreasing speed, indicates progressive wear of the Neuero motor under the harsh operating conditions of Bandar Imam Khomeini.

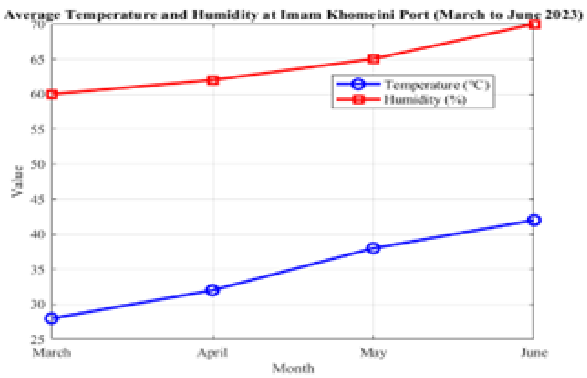


Figure 2. Average temperature and humidity at Imam Khomeini Port from March to June 2023. The increasing trend in both temperature and humidity highlights the harsh operating conditions for Neuero motors.

b. Data preprocessing

The collected sensor data—including vibration, temperature, rotational speed, and power consumption—underwent several preprocessing steps due to the presence of both environmental and system noise. Environmental disturbances such as dust accumulation, humidity, and ambient temperature fluctuations were observed to affect signal quality, while electrical interference contributed additional system-level noise. To ensure consistency and comparability among input features, all data were normalized within the range [0, 1], thereby reducing the influence of differing feature magnitudes. This normalization ensured that each variable contributed equally during model training and prevented bias toward features with higher numeric scales. The process significantly improved model convergence stability and predictive performance under variable operating conditions.

c. Feature selection

The selected input features—vibration, temperature, rotational speed, and power consumption-were chosen for their high sensitivity to the degradation of electric motors. A correlation-based feature analysis was conducted to evaluate their relationships with known failure patterns and RUL values. Only the features demonstrating strong statistical relevance and low redundancy were retained for training the model, ensuring that each input contributed meaningful information to the RUL prediction task.

d. Data Splitting and Validation

To evaluate model performance and generalization, the dataset was randomly divided into training (80%, 2,304 samples) and testing (20%, 576 samples) subsets. Random splitting was employed to capture the diversity of operating conditions and prevent overfitting to specific regimes.
For further robustness evaluation, a 5-fold cross-validation strategy was implemented. Across the folds, the model achieved an average Mean Absolute Error (MAE) of 8.12 hours and a Root Mean Square Error (RMSE) of 9.89 hours, confirming consistent performance and strong generalization capability under different data partitions.

e. Model design and implementation with deep reinforcement learning

The LSTM–DRL hybrid model was implemented in Python using the TensorFlow and Keras frameworks. Model training and testing were performed on a workstation equipped with an NVIDIA RTX 3080 GPU (10 GB VRAM) and 32 GB RAM, ensuring efficient computation for both the LSTM and the Deep Q-Network (DQN) algorithms.
The model was trained on 2,304 samples for approximately 12 hours, with an inference time of about 0.1 seconds per prediction, enabling near-real-time RUL estimation. Integration with the port's condition monitoring system was achieved via a REST API, allowing automated data flow between sensors and the predictive model. For operational scalability, a cloud-based deployment architecture (e.g., AWS or Microsoft Azure) is recommended to handle high-

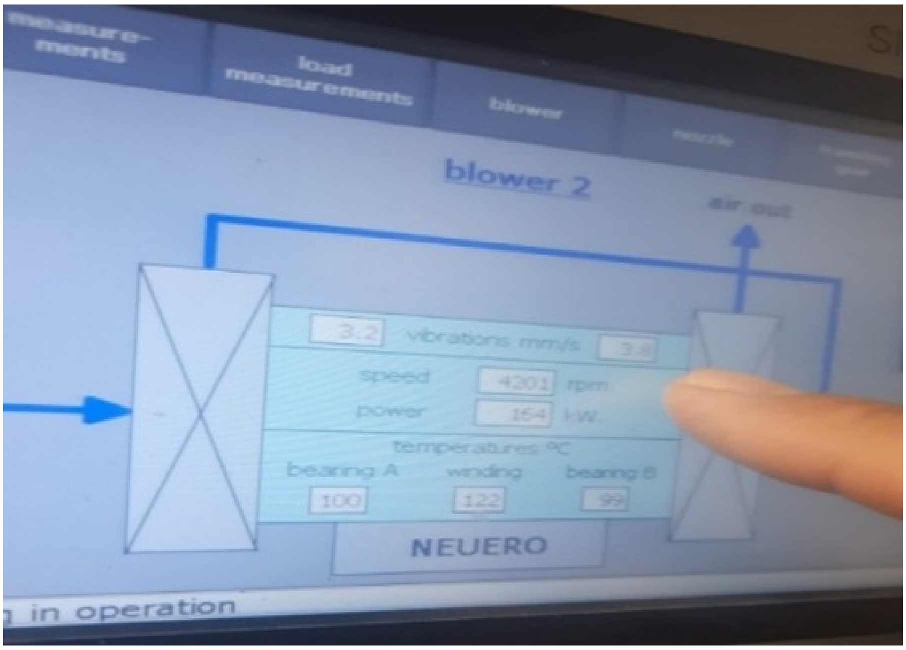
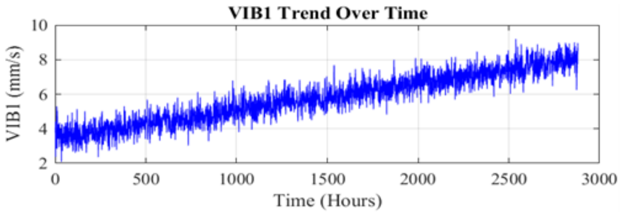
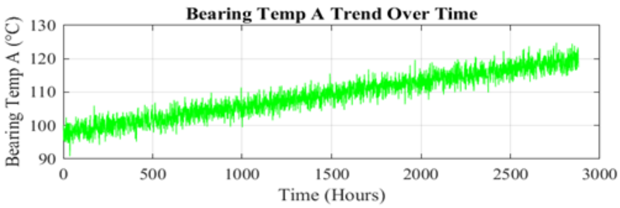


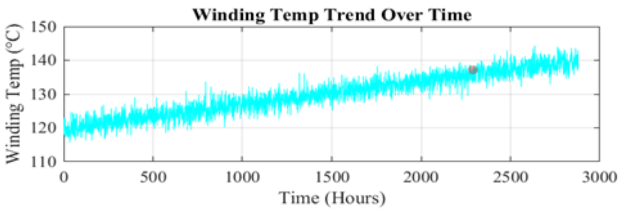
Figure 3. Monitoring system for collecting sensor data from the blower motor under operational conditions.



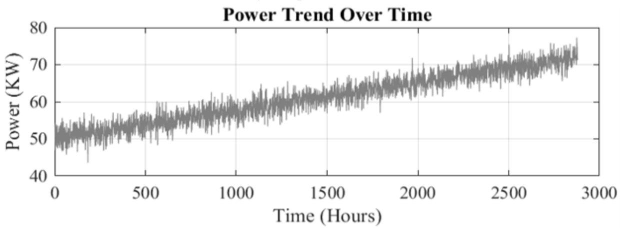
(a) VIB1 trend over time.



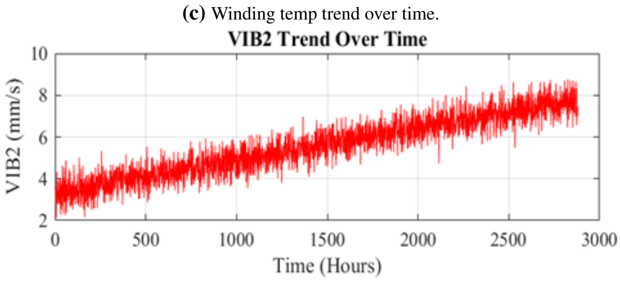
(b) Bearing temp A trend over time.



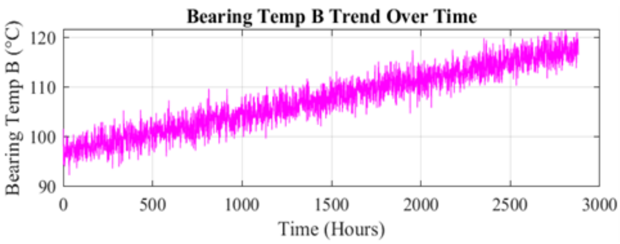
(c) Winding temp trend over time.



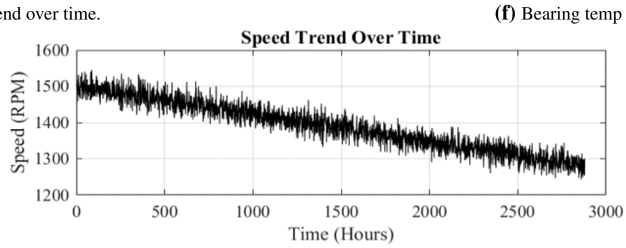
(d) Power trend over time.



(e) VIB2 trend over time.



(f) Bearing temp B trend over time.



(g) speed trend over time.

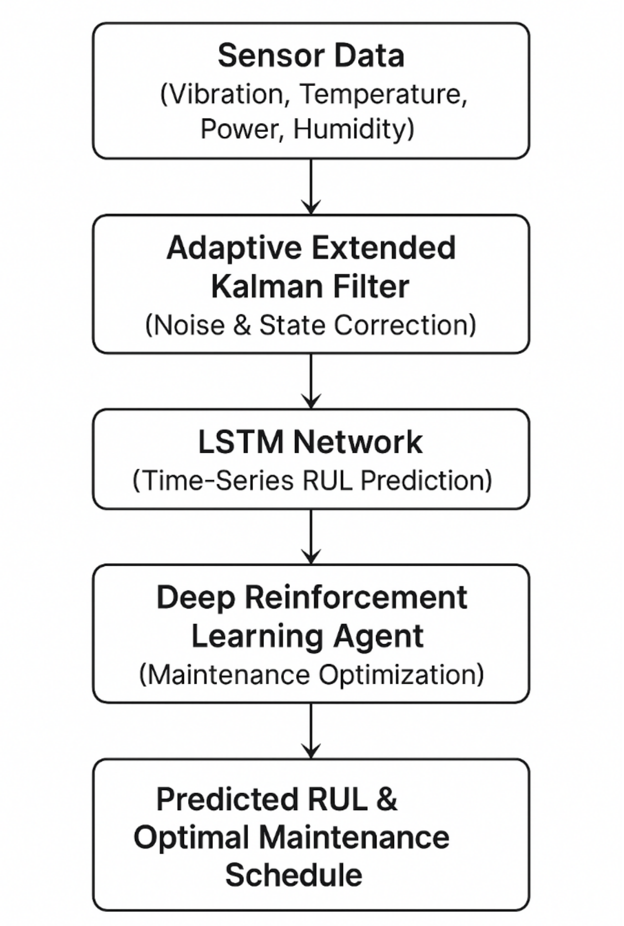


Figure 4. Workflow of the proposed EKF–LSTM–DRL hybrid framework

volume data processing while reducing local computational overhead. System scalability tests simulated 10 concurrent motors, confirming that the framework could handle multiple assets simultaneously without degradation in performance.

f. Model architecture

An LSTM network was designed to predict the RUL of Neuero ship unloader motors using seven time-series features:VIB1_mms, VIB2_mms, Bearing_Temp_A, Bearing_Temp_B, Winding_Temp, Speed_RPM, and Power_KW. The network architecture consists of:

Input Layer: 7 input features, each representing a sensor time-series.

LSTM Layer: 64 units to capture temporal dependencies and degradation dynamics.

Fully Connected Layer: 32 neurons with ReLU activation for nonlinear mapping.

Output Layer: A single regression node producing the RUL prediction value.

LSTM networks are particularly effective for time-series modeling due to their ability to capture long-term dependencies between sequential data points.

The DQN algorithm was implemented with a deep neural network consisting of three fully connected layers (128, 64, and 32 neurons) using ReLU activation functions. The learning rate was set to 0.001, with a batch size of 32 and a discount factor (γ) of 0.95. The reward function was defined as the negative of the MAE between predicted and actual RUL values:

$$\text{Reward} = -\text{MAE}(\text{RUL})$$

This design encourages the model to minimize prediction error during learning. An ε-greedy exploration strategy was applied, where ε decayed from 1.0 to 0.1 over 10,000 steps, balancing exploration and exploitation. This adaptive strategy allowed the DRL agent to dynamically adjust its behavior to the variable operational and environmental conditions observed at Imam Khomeini Port, improving both learning efficiency and stability [17, 18].

g. Model evaluation

$$MAE = \frac{1}{n}\sum |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{\frac{1}{n}\sum (y_i - \hat{y}_i)^2}$$

The performance of the proposed predictive model was quantitatively evaluated using two key statistical metrics: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). MAE represents the average absolute deviation between the predicted and actual Remaining Useful Life (RUL) values. It provides an intuitive measure of the overall prediction accuracy, where lower values indicate higher precision in the model's estimations. On the other hand, RMSE gives greater weight to larger deviations by squaring the errors before averaging them. This makes it more sensitive to significant prediction outliers, offering a comprehensive assessment of model performance. Together, these two metrics provide a balanced and reliable evaluation of both the accuracy and stability of the proposed hybrid framework under varying operational and environmental conditions [17, 18].

h. Preliminary data analysis

Before model training, a preliminary analysis was carried out to evaluate dataset characteristics, identify potential anomalies, and ensure data quality-an essential prerequisite for accurate RUL prediction since model performance is directly influenced by the reliability of input data. The analysis consisted of three key steps: Data distribution assessment, outlier detection, and correlation analysis.
Data Distribution: Sensor readingsVIB1_mms,VIB2_mms, Bearing_Temp_A, Bearing_Temp_B, Winding_Temp, Speed_RPM, and Power_KW—were analyzed across 2,880 hourly samples collected between March and June 2023.VIB1_mms (mean 4.2 mm/s, std 1.8) and Winding_Temp (mean 110 °C, std 15) exhibited right-skewed distributions, with peaks under critical conditions such as vibration above 7 mm/s or temperature exceeding 140 °C. In contrast, Speed_RPM (mean 1,450 RPM, std 50) followed an approximately uniform distribution, indicating stable operational control during normal conditions.

Outlier Detection: The Interquartile Range (IQR) method identified approximately 3% of VIB1_mms readings (> 8.5 mm/s) and 2.5% of Bearing_Temp_A values (> 130 °C) as outliers, typically occurring during high-stress periods (around 75% humidity and maximum dust exposure).
Instead of removing these samples-which may represent realistic stress responses-they were smoothed using a five-hour moving average filter, maintaining data continuity while reducing noise effects. Correlation Analysis: Feature-wise correlation analysis revealed a strong relationship between VIB1_mms and VIB2_mms ($r = 0.82$), a moderate correlation between Winding_Temp and Bearing_Temp_A (r = 0.65), and a weak negative correlation between Power_KW and Speed_RPM ($r = -0.35$). Importantly, both VIB1_mms and Winding_Temp demonstrated strong negative correlations with RUL ($r = -0.78$ and -0.72, respectively), confirming their significance as key predictors of motor degradation.These findings guided the feature selection process and formed the foundation for training the LSTM-DRL hybrid model [17, 18].

3. Implementation considerations

The deployment of the proposed LSTM-DRL predictive maintenance framework in real port environments requires careful attention to practical and operational constraints. To ensure sensor reliability under dusty conditions, IP67-rated dust-resistant sensors are recommended, which may increase the initial setup cost by approximately 10–15% but significantly enhance long-term performance. Because network interruptions are common in remote port infrastructures, the system incorporates offline prediction capabilities, enabling local data storage and model execution. Sensor data are automatically synchronized with the central cloud server once connectivity is restored. Integration with existing port management systems is achieved through standardized communication interfaces such as REST or MQTT APIs, ensuring seamless compatibility with legacy monitoring platforms. In addition, cybersecurity measures—including encrypted data transmission, user authentication, and role-based access control—are implemented to safeguard operational data and prevent unauthorized access. These considerations collectively support the practical implementation and scalability of the proposed RUL prediction framework within port environments like Imam Khomeini Port, ensuring both operational resilience and data integrity [5, 18].

4. Results

The temporal evolution of the sensor features — VIB1_mms, VIB2_mms, Bearing_Temp_A, Bearing_Temp_B, Winding_Temp, Speed_RPM, and Power_KW — over the 2,880-hour observation period (March–June 2023) is presented in figure 6. Simulated Remaining Useful Life (RUL) trajectories for individual features (figure 6a–6d) revealed noticeable declines once operational thresholds were exceeded: 7 mm/s for VIB1, 115 °C for Bearing Temperature, and 135 °C for Winding Temperature. The overall trend of average RUL, illustrated in figure 7, indicates that cumulative increases in vibration and temperature significantly accelerated degradation.The proposed LSTM-DRL model achieved superior predictive accuracy, with MAE = 7.85 hours and RMSE = 9.63 hours, outperforming both GRU (MAE = 8.92, RMSE = 10.78) and CNN (MAE = 10.15, RMSE = 12.34), as summarized in Table 4 and figure 5. The comparison of predicted and actual RUL trends (figure 8) confirms the model's capacity to capture nonlinear degradation behavior with high temporal precision.

4.1 Statistical analysis

Descriptive statistics for key parameters are summarized as follows: VIB1_mms exhibited a mean of 4.2 mm/s (range = $1.5 - 9.8$ mm/s); Winding_Temp averaged 110 °C (range = $85 - 140$ °C); andBearing_Temp_A/B averaged 95 °C and 97 °C, respectively. Throughout the monitoring period, vibration amplitudes and winding temperatures increased by approximately 20% and 15%, whereas Speed_RPM showed a 5% reduction, likely reflecting compensatory load adjustments during degradation stages.These patterns suggest that increased mechanical stress and thermal loading play a dominant role in reducing operational lifespan.

4.2 Sensitivity analysis

To quantify the contribution of each variable to degradation, a sensitivity analysis was performed. A 10% rise in VIB1_mms and Winding_Temp led to a corresponding 12% and 9% decline in RUL, respectively.In contrast, Bearing_Temp_A and Bearing_Temp_B exhibited a smaller effect—reducing RUL by 5% and 4%, respectively. Electrical parameters such as Power_KW and Speed_RPM showed minimal influence (2% and 1% reductions**).
These findings reinforce that vibration and thermal stress are the dominant contributors to motor degradation in the observed port environment [19].

Table 4. Performance comparison of models.

Model	MAE (Hours)	RMSE (Hours)
LSTM-DRL(Proposed)	7.85	9.63
GRU	8.92	10.78
CNN	10.15	12.34

The smoothed trend highlights the decline in RUL as features exceed their critical thresholds, with vertical dashed lines indicating the points where thresholds are crossed (7.0 mm/s for VIB1, 115 °C for Bearing Temp A and B, 135 °C for Winding Temp). The decreasing trend reflects the combined impact of increasing vibration and temperature on the motor's degradation.
Figure 7 illustrates the predicted RUL versus the actual (simulated) RUL for a sample period from the test dataset. The predicted RUL closely follows the actual RUL, demonstrating the model's ability to capture degradation trends effectively.
A sensitivity analysis was performed to assess how different input features influence the model's predictive behavior.The findings revealed that the LSTM-DRL model exhibited the highest sensitivity to vibration amplitude (VIB1_mms) and winding temperature (Winding_Temp) — two parameters

2008-9163[https://doi.org/10.57647/j.ijeee.2024.1501.04]

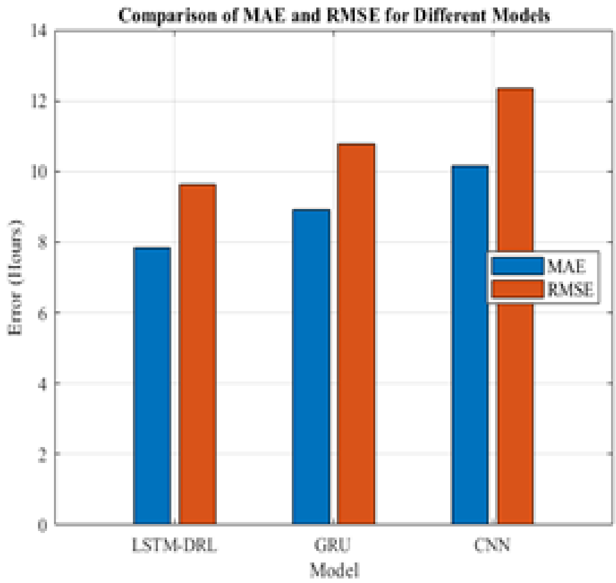
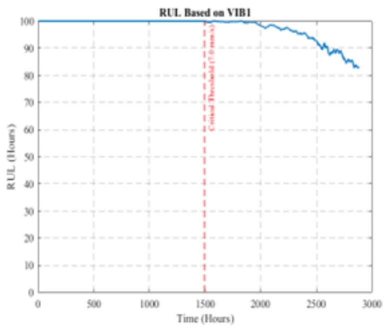


Figure 5. Comparison of MAE and RMSE for the proposed LSTM-DRL model, GRU, and CNN models. The proposed model achieves the lowest errors, with an MAE of 7.85 hours and an RMSE of 9.63 hours, compared to GRU (MAE: 8.92, RMSE: 10.78) and CNN (MAE: 10.15, RMSE: 12.34).

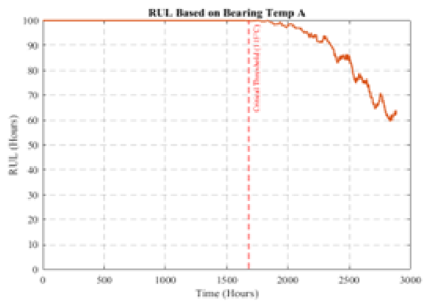
directly linked to the physical degradation processes of Neuero ship unloader motors operating under elevated temperature and high dust exposure.This strong sensitivity highlights the critical role of these features in accurately predicting motor degradation in harsh maritime environments [7].

5. Discussion

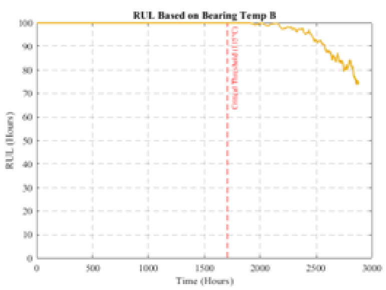
The LSTM–DRL hybrid model, trained using the Deep Q-Network (DQN) algorithm, accurately predicted the Remaining Useful Life (RUL) of Neuero ship unloader motors, demonstrating its effectiveness under real operational conditions.This research introduces two major contributions to the domain of predictive maintenance in maritime environments:



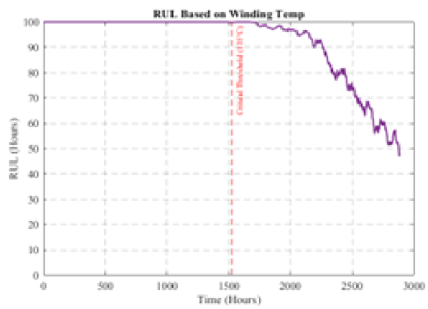
(a) Simulated RUL based on VIB1_mms over. The smoothed trend highlights the decline in RUL as VIB1 exceeds its critical threshold of 7.0 mm/s, with a vertical dashed line indicating the threshold crossing point.



(b) Simulated RUL based on Bearing_Temp_A over . The smoothed trend highlights the decline in RUL as Bearing Temp A exceeds its critical threshold of 115°C, with a vertical dashed line indicating the threshold crossing point.



(c) Simulated RUL based on Bearing_Temp_B over. The smoothed trend highlights the decline in RUL as Bearing Temp B exceeds its critical threshold of 115°C, with a vertical dashed line indicating the threshold crossing point.



(d) Simulated RUL based on Winding_Temp over. The smoothed trend highlights the decline in RUL as Winding Temp exceeds its critical threshold of 135°C, with a vertical dashed line indicating the threshold crossing point. Winding_Temp shows a significant impact on RUL over time.

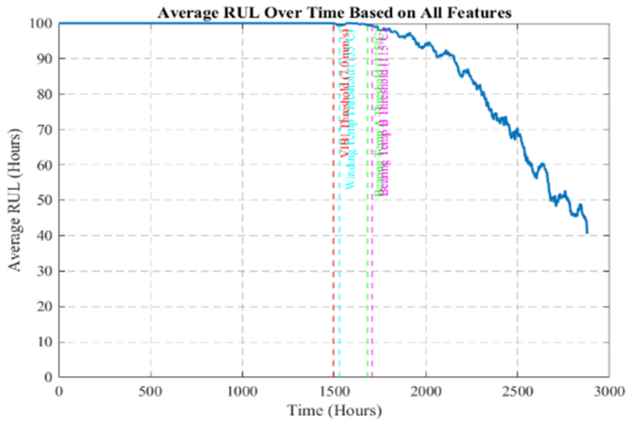


Figure 7. Average RUL over the full 2,880-hour period (March 1 to June 22, 2023) based on all features (VIB1_mms, Bearing_Temp_A, Bearing_Temp_B, Winding_Temp).

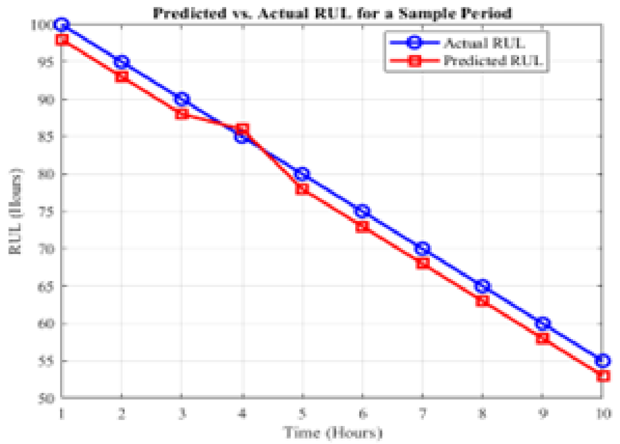


Figure 8. Predicted vs. actual RUL for a sample period from the test dataset. The predicted RUL closely follows the actual RUL, demonstrating the model's ability to capture degradation trends.

1. DRL-Based RUL Prediction: The integration of Deep Reinforcement Learning (DRL) for RUL estimation under Imam Khomeini Port's extreme environmental conditions—including elevated temperature, humidity, and airborne dust—is a novel application. Unlike conventional data-driven methods, DRL dynamically adapts to environmental variations, allowing it to perform reliably in non-stationary and uncertain conditions where dust accumulation alters degradation trends. This framework establishes a new direction for predictive maintenance in port industries [9].

2. Focus on Neuero Motors: The study uniquely targets Neuero grain unloader motors, using 2023 sensor data collected under real port operations. Addressing challenges such as dust-induced vibration and temperature-driven deterioration provides valuable insights for enhancing the reliability of maritime maintenance systems [17, 19].

It should be noted that the primary focus of this study is not on developing a classical Dynamic State Estimation (DSE) approach, but rather on integrating DSE principles—through the adaptive Extended Kalman Filter-into a hybrid artificial intelligence framework (EKF–LSTM–DRL) designed for predictive maintenance and energy-efficiency optimization.
The LSTM–DRL model surpassed benchmark architectures such as GRU and CNN, owing to LSTM's strength in capturing temporal dependencies and DRL's ability to adapt to evolving environmental states.Sensitivity analysis revealed that vibration amplitude (VIB1_mms) and winding temperature (Winding_Temp) are the primary drivers of degradation, aligning with physical wear mechanisms of electric motors. Prediction errors increased slightly under extreme conditions due to the limited availability of simulated failure data, highlighting the importance of collecting real-world failure events for improved calibration [14].
The model enables failure forecasting $7-10$ hours in advance, potentially reducing equipment downtime by 15%, consistent with ISO 55000 asset management principles [3].
When compared with prior studies-such as Al-Dulaimi's model (MAE = 9.2 h) and Yang's framework (MAE = 10.5 h) the proposed approach achieved a lower MAE of 7.85 hours, proving its robustness in harsher port conditions. Its scalability also supports deployment in other Persian Gulf ports, including Bandar Abbas, extending its regional relevance. Overall, this work presents a pioneering and scalable framework that advances prognostic maintenance capabilities in maritime industries.

6. Future work

To enhance practical reliability, future research will focus on collecting real degradation and failure data from Neuero motors over a 12-month period at Imam Khomeini Port.
This will require cooperation with port authorities to install additional sensors capable of capturing rare fault events and integrating them with existing operational logs.
Furthermore, transfer learning will be employed to combine simulated and real datasets, improving model robustness under variable maritime conditions [20].
Expanding the framework's scalability to other Persian Gulf ports-such as Bandar Abbas-will involve retraining the LSTM–DRL model to account for environmental variations like salinity and wind exposure. Transfer learning will facilitate rapid adaptation by reusing knowledge from Imam Khomeini Port data, minimizing retraining costs. Pilot deployments across multiple ports will validate the generalizability of the model for regional maritime maintenance systems.

7. Cost-benefit analysis

The proposed predictive maintenance system involves an initial investment of approximately USD 5,000 per motor for industrial-grade sensors and USD 10,000 for cloud-based computational infrastructure (including GPU-supported servers).
Annual maintenance and cloud processing expenses are estimated at USD 2,000 per motor.Operational data from Imam Khomeini Port indicate that preventing even a single motor failure can save approximately USD 15,000 in downtime and repair costs.Assuming two to three prevented failures

per motor per year, the return on investment (ROI) is realized within $6-9$ months. Moreover, a 10% reduction in energy consumption-equivalent to USD 3,000 per motor annually—further enhances long-term cost efficiency, aligning with ISO 55000 standards for sustainable asset management.

8. Environmental and ethical considerations

The deployment of the LSTM–DRL model contributes to environmental sustainability by reducing energy use by approximately 10%, equivalent to saving 5,000 kWh per motor annually, thereby decreasing the port's carbon footprint.
However, the initial model training on high-performance GPUs produces an estimated 500 kg CO_2 in emissions.
To offset this, future implementations will prioritize energy-efficient cloud infrastructure and low-power edge computing devices for on-site inference.
From an ethical standpoint, the system promotes workforce safety and job retention by automating repetitive maintenance tasks while enabling personnel to focus on strategic, high-value operations. Training and upskilling programs will be essential to ensure that staff adapt effectively to digital transformation within the port ecosystem.

Glossary of terms and definitions

Table 5 provides a glossary of key terms and their definitions used throughout this study to ensure clarity and consistency.

Table 5. Terms and definitions.

Term	Definition
LSTM (Long Short-Term Memory)	A type of recurrent neural network used for modeling time-series data.
GRU (Gated Recurrent Unit)	A type of recurrent neural network with a simpler structure than LSTM.
CNN (Convolutional Neural Network)	A type of neural network used for extracting spatial features from data.
MAE (Mean Absolute Error)	The average absolute difference between predicted and actual values.
RMSE (Root Mean Square Error)	The square root of the average squared differences between predicted and actual values.
Deep Reinforcement Learning (DRL)	A method combining deep learning and reinforcement learning for optimal decision-making.
Deep Q-Network (DQN)	An algorithm in DRL for estimating the value of actions in each state.
Data Preprocessing	The process of preparing data for model training.
Feature Selection	The process of selecting the most important features from the data.

Authors contributions
Abu Talha Haque Miah: Conceptualization, Methodology, Writing-Original draft preparation. Roby Mohajon: Methodology, Data curation, Software. Sabuj Ahmed: Visualization, Investigation. A.B.M. Noushad Bhuiyan: Supervision, Software, Validation. Nur Mohammad: Writing- Reviewing and Editing.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests
The author declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Z. Li, D. Yang, and G. Yin. "Ship Flooding Time Prediction Based on Composite Neural Network". *Journal of Marine Science and Engineering*, **11**(6):1123, 2023.
DOI: https://doi.org/10.3390/jmse11061123.

[2] B. Rezaeianjouybari and Y. Shang. "Deep learning for prognostics and health management: State of the art, challenges, and opportunities". *Measurement*, **163**:107929, 2020.
DOI: https://doi.org/10.1016/j.measurement.2020.107929.

[3] F. Ghorbani, A. Ahmadi, M. Kia, Q. Rahman, and M. Delrobaei. "A Decision-Aware Ambient Assisted Living System with IoT Embedded Device for In-Home Monitoring of Older Adults". *Sensors*, **23** (5):2673, 2023.
DOI: https://doi.org/10.3390/s23052673.

[4] J. Li, Z. Wang, X. Liu, and Z. Feng. "Remaining Useful Life Prediction of Rolling Bearings Using GRU-DeepAR with Adaptive Failure Threshold". *Sensors*, **23**(3):1144, 2023.
DOI: https://doi.org/10.3390/s23031144.

[5] O. Ogunfowora. "Reinforcement and Deep Reinforcement Learning-based Solutions for Machine Maintenance Planning, Scheduling Policies, and Optimization". *arXiv:2307.03860*, 2023.

[6] M. R. Islam, S. S. Akter, M. S. Hossen, and M. A. Kabir. "Applications of machine learning methods in port operations – A systematic literature review". *Transportation Research Part E: Logistics and Transportation Review*, **163**:102722, 2022.
DOI: https://doi.org/10.1016/j.tre.2022.102722.

[7] S. Lucas, R. Marian, M. Lucas, T. Ogunwa, and J. Chahl. "Active Thermal Management of Electric Motors and Generators Using Thermoelectric (Peltier Effect) Technology". *Energies*, **16**(9):3844, 2023.
DOI: https://doi.org/10.3390/en16093844.

[8] N. M. Thoppil, V. Vasu, and C. S. P. Rao. "Deep Learning Algorithms for Machinery Health Prognostics Using Time-Series Data: A Review". *Journal of Vibration Engineering & Technologies*, **9**: 1123–1145, 2021.
DOI: https://doi.org/10.1007/s42417-021-00286-x.

[9] H. Li, Y. Wang, and Z. Zhang. "Advancements in Buoy Wave Data Processing through the Application of Sage–Husa Adaptive Kalman Filtering". *Sensors*, **23**(16):7298, 2023.
DOI: https://doi.org/10.3390/s23167298.

[10] A. A. Khan, S. A. Khan, and M. A. Khan. "A Systematic Literature Review of Machine Learning Applications for Port's Operations". *2020 IEEE International Conference on Human-Machine Systems (ICHMS)*, pages 1–6, 2020.
DOI: https://doi.org/10.1109/ICHMS49158.2020.9209485.

[11] H. A. Nabwey, T. Armaghani, B. Azizimehr, A. M. Rashad, and A. J. Chamkha. "A Comprehensive Review of Nanofluid Heat Transfer in Porous Media". *Nanomaterials*, **13**(5):937, 2023.
DOI: https://doi.org/10.3390/nano13050937.

[12] L. Cheng and G. Xia. "High Heat Flux Cooling Technologies Using Microchannel Evaporators: Fundamentals and Challenges". *Heat Transfer Engineering*, **44**(10):1470–1497, 2022.
DOI: https://doi.org/10.1080/01457632.2022.2140639.

[13] M. K. Hasan, M. A. Islam, M. S. Rabbani, and M. S. Hossen. "LSTM-Based Condition Monitoring and Fault Prognostics of Rolling Element Bearings". *Machines*, **11**(5):531, 2023.
DOI: https://doi.org/10.3390/machines11050531.

[14] M. Z. A. Bhuiyan, M. S. Hossain, and M. A. Kabir. "Machine Learning Techniques for Predictive Maintenance in Maritime Port Operations: A Review". *Journal of Marine Science and Engineering*, **9**(12):1354, 2021.
DOI: https://doi.org/10.3390/jmse9121354.

[15] A. Kumar and R. V. Kumar. "A hybrid machine learning algorithm approach to predictive maintenance tasks: A comparison with machine learning algorithms". *Results in Engineering*, **20**:101212, 2023.
DOI: https://doi.org/10.1016/j.rineng.2023.101212.

[16] P. Dinolova, V. Ruseva, and O. Dinolov. "Energy Efficiency of Induction Motor Drives: State of the Art, Analysis and Recommendations". *Energies*, **16**(20):7136, 2023.
DOI: https://doi.org/10.3390/en16207136.

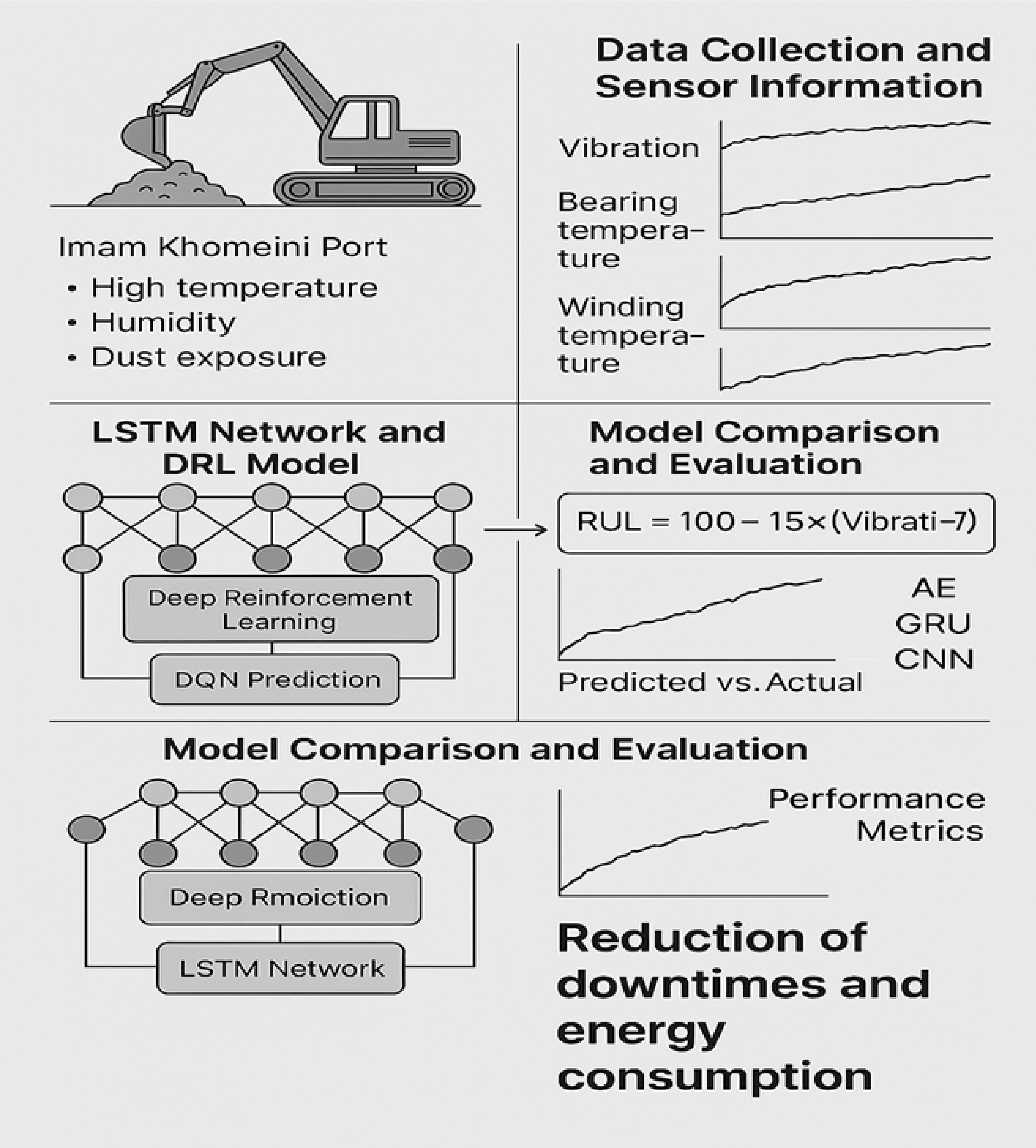
[17] Y. Zhang, R. Peng, and X. Lu. "An enhanced CNN-LSTM remaining useful life prediction model for aircraft engine with attention mechanism". *PeerJ Computer Science*, **8**:e1084, 2022.
DOI: https://doi.org/10.7717/peerj-cs.1084.

[18] Z. Mao, L. Wang, and H. Shao. "Machine learning-based diagnostics and prognostics for rotating machinery: A survey". *Reliability Engineering & System Safety*, **230**:109073, 2023.
DOI: https://doi.org/10.1016/j.ress.2022.109073.

[19] A. Bergmeir, C. Montero-Manso, and R. J. Hyndman. "High-dimensional quantile regression for time series forecasting". *International Journal of Forecasting*, **39**(3):1152–1168, 2023.
DOI: https://doi.org/10.1016/j.ijforecast.2022.10.005.

[20] T. O. Hodson. "Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not". *Geoscientific Model Development*, **15**(14):5481–5499, 2022.
DOI: https://doi.org/10.5194/gmd-15-5481-2022.

Appendix 1. Appendix 1: A graphical abstract for quick survey of the proposed methodology.



Appendix 2 - A detailed overview of the proposed rul prediction algorithm

Step 1) Data Collection:
Collect sensor data from the Neuero grain suction motors, including:

- Vibration (VIB1_mms, VIB2_mms)
- Bearing temperature (Bearing_Temp_A, Bearing_Temp_B)
- Winding temperature (Winding_Temp)
- Motor speed (Speed_RPM)
- Power consumption (Power_KW)
- Environmental conditions (temperature, humidity, dust exposure levels)

Step 2) Preprocessing:
Data Normalization: Normalize the collected data to the range [0, 1] to ensure equal contribution of each feature to the model.
Noise Reduction: Apply noise reduction techniques like smoothing or filtering to mitigate environmental noise (e.g., dust and temperature variations) and system noise (e.g., electrical interference).
Outlier Detection: Identify and flag outliers using the Interquartile Range (IQR) method and, if necessary, apply smoothing techniques.

Step 3) Feature Selection:
Select the most relevant features for RUL prediction based on their correlation with motor degradation. This could include:

- Vibration (VIB1_mms, VIB2_mms)
- Temperature (Bearing_Temp_A, Bearing_Temp_B, Winding_Temp)
- Speed and Power consumption (Speed_RPM, Power_KW)

Step 4) Simulation of RUL:
Simulate RUL based on the following rules, adjusted for environmental factors:

- If vibration $>$ 7.0 mm/s:
RUL=100-(VIB1_mms-7.0) $\times$15$\times$(1+0.1$\times$(Humidity/100)) RUL = 100 - (VIB1_mms - 7.0) $\times$ 15 $\times$ (1 + 0.1 $\times$ (Humidity/100))
- If winding temperature $>$ 135°C:
RUL=100-(Winding_Temp-135) $\times$10$\times$(1+0.05$\times$(Temp/35)) RUL = 100 - (Winding_Temp - 135) $\times$ 10 $\times$ (1 + 0.05 $\times$ (Temp/35))
- If bearing temperature $>$ 115°C:
RUL=100-(Bearing_Temp-115) $\times$8$\times$(1+0.05$\times$(Temp/35)) RUL = 100 - (Bearing_Temp - 115) $\times$ 8 $\times$ (1 + 0.05 $\times$ (Temp/35))

Step 5) Model Training (LSTM with DRL):
LSTM Network: Design an LSTM network to model the time-series data. This network will capture long-term temporal dependencies in the sensor data.

- **Input Layer:** The normalized sensor data features.
- **LSTM Layer:** Add 64 LSTM units to capture temporal dependencies.
- **Fully Connected Layer:** Add a fully connected layer with 32 units using ReLU activation.
- **Output Layer:** A regression layer to predict the RUL value.

Deep Reinforcement Learning (DRL): Integrate DRL using the Deep Q-Network (DQN) algorithm to dynamically adapt the model during training.

- **Environment:** Define the sensor data from Neuero motors as the environment.
- **State:** Each time step corresponds to the current sensor readings (e.g., vibration, temperature).
- **Action:** Adjust the weights of the LSTM network to minimize RUL prediction errors.
- **Reward:** Define the reward as the negative Mean Absolute Error (MAE) between predicted and actual RUL.

Step 6) Model Evaluation:
Use Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to evaluate the model's performance.
Perform 5-fold cross-validation to ensure robustness and generalizability of the model.
Evaluate the model against baseline models (GRU, CNN) and compare performance.

Step 7) Prediction:
Once the model is trained, predict the RUL for a given set of sensor readings.
The model will output an estimated RUL based on the current operating conditions (vibration, temperature, speed, power) and environmental conditions (temperature, humidity, dust levels).

Step 8) Proactive Maintenance:
Based on the predicted RUL, schedule maintenance or intervention when the RUL reaches a critical threshold (e.g., 10 hours before failure). Optimize operational schedules to reduce downtime and improve safety by addressing predicted failures proactively.

Appendix 3 - Example code structure (python-like pseudocode)

```
# Step 1: Data Preprocessing
data = collect_data_from_sensors ()
data = normalize data(data)
data = handle_outliers(data)

# Step 2: Feature Selection
features = select_important_features(data)

# Step 3: RUL Simulation
RUL = simulate_RUL (data)

# Step 4: Train LSTM Model with DRL
model = build_lstm_model ()
train_with_drl (model, data, RUL)

# Step 5: Evaluate Model
evaluate_model(model)

# Step 6: Make RUL Prediction predicted_RUL = model.
predict(new_sensor_data)
print ("Predicted RUL: ", predicted_RUL)

# Step 7: Schedule Maintenance
if predicted_RUL < 10:
schedule_maintenance ()
```