INTERNATIONAL JOURNAL OF MARITIME TECHNOLOGY

IJMT Vol.20 / Summer& Autumn 2024 (61-69)

Available online at: www. ijmt.ir

A data-driven artificial intelligence approach to predict the remaining useful life of Neuero grain unloaders in Khuzestan ports

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ARTICLE INFO

Article History:
Received: 18 Oct 2024
Accepted: 06 Jan 2025
Available online: 07 Jan 2025

Keywords:
Remaining Life Prediction
Failure Process Modeling
Neural Networks
Artificial Intelligence
Data-Driven Approach.

ABSTRACT

This study aims to enhance equipment management in grain unloading operations at Khuzestan Ports in Iran by predicting the remaining useful life of electric motors used in grain suction systems (neuero). Utilizing LSTM models in conjunction with environmental factors, this research minimizes unexpected costs associated with equipment failures and reduces downtime in unloading and loading processes. Real-world data from Khuzestan ports demonstrates the high accuracy of the LSTM model in predicting failures. The findings support proactive maintenance strategies, thereby improving efficiency and reliability in the port and maritime industry. While challenges such as limited data, incomplete coverage of environmental factors, and reliance on deep learning models exist, this study provides a foundation for future research on optimizing maintenance and management of neuero electric motors in bulk vessels.

1. Introduction

In the past few decades, significant strides in machine learning have given rise to a multitude of applications across diverse industries. The maritime and navigation sector is one such area that has greatly benefited from these advancements. Essential equipment, such as electric motors, serve a pivotal role, akin to the heart and brain, within the grain crystal blender facilities at ports and maritime organizations.

Electric motors, integral to the functioning of grain crystal blenders in ports and navigation, are critical for power supply and execution of primary tasks. However, predicting their failures and remaining lifespan poses a significant challenge in managing these devices.

This research is dedicated to enhancing the management and boosting the efficiency of electric equipment through the application of advanced modeling and prediction methodologies. By employing deep learning algorithms and artificial intelligence neural networks, the study endeavors to identify fault patterns and predict failure times with greater precision. Concurrently, an analysis of factors influencing the failure of electric motors, including environmental conditions and external factors, is undertaken. This approach is crucial to augmenting the model's accuracy in addressing real-world conditions in the ports and navigation industry.

The significance of this research is underscored by the creation of pioneering methodologies for failure prediction and the enhancement of equipment performance within the industrial sector. These advancements will equip organizations and industries with the tools to diminish expenses and augment efficiency through the execution of optimization and maintenance strategies. Subsequent sections of this article will delineate the technologies and methodologies introduced, analyze the results, and propose recommendations for future research. This study plays a pivotal role in the ongoing efforts to bolster productivity and reliability across a multitude of industries.

2. Literature Survey

Mohammad Saeed Saif and colleagues: investigate the application of artificial intelligence in predicting marine equipment failures. This article first introduces various predictive methods for equipment failure and then examines the advantages and disadvantages of using artificial intelligence for this purpose. Finally, several examples of artificial intelligence applications in predicting marine equipment failures are presented.[1]

Ahmad Reza Ahmadi and colleagues: focus on examining the reliability of marine propulsion systems using simulation methods. In this article, the introduction of marine propulsion systems and the factors affecting their reliability are discussed. Then, various simulation methods for evaluating the reliability of these systems are introduced. Finally, a case study of simulating the reliability of a marine propulsion system is presented.[2]

Sara Mohammadi and colleagues: propose a new model for preventive maintenance of marine equipment. This model is designed based on machine learning and utilizes data related to past equipment failures. The results show that this model can significantly increase the accuracy of predicting marine equipment failures, thereby reducing repair and maintenance costs and enhancing equipment reliability.[3]

Mehdi Rezaei and colleagues: examine the application of artificial intelligence in the field of ship repair and maintenance. In this article, various ship repair and maintenance methods and the challenges in this field are introduced. Then, the advantages and disadvantages of using artificial intelligence for ship repair and maintenance are discussed. Finally, several examples of artificial intelligence applications in ship repair and maintenance are presented.[4]

Ali Mohammadi and colleagues: investigate the impact of artificial intelligence on the maritime industry. This article first introduces artificial intelligence and its applications in various fields. Then, the advantages and disadvantages of using artificial intelligence in the maritime industry are examined. Finally, some of the challenges and opportunities for the use of artificial intelligence in this industry are highlighted. The results of this article show that artificial intelligence can be applied in various maritime industry sectors, such as navigation, maritime operations, repair and maintenance, and ship design, contributing to increased safety, efficiency, and stability in the maritime industry.[5]

Mehdi Rezaei and colleagues: present an artificial intelligence-based system for monitoring the status of marine equipment. In this article, various methods of monitoring the status of equipment and the existing challenges in this field are introduced. Then, the advantages and disadvantages of using artificial intelligence for monitoring the status of marine equipment are examined. Finally, a new artificial intelligence-based system for monitoring the status of marine equipment is presented. The results of this article demonstrate that the proposed system can accurately monitor the status of marine equipment, contributing to increased efficiency.[6]

2-1 Research background

With the rapid development of advanced technologies such as sensors, storage, edge computing, communications, and signal processing, a large amount of condition monitoring (CM) data, which is related to the health status of equipment, enables the rapid development of data-driven approaches for RUL prediction. Data-driven approaches for RUL prediction can be divided into statistical approaches and machine learning-based approaches.

Statistical approaches require building degradation models based on the studied targets. For example, Jin et al. developed a bearing degradation model. They used the extended Kalman filter to update the model parameters and then predicted the RUL of the bearing based on it. [7] Huang et al. used an adaptive skew-Wiener model to describe the degradation drift and predict the RUL of an industrial machine. It is worth noting that many degradation models can be built to fit specific case studies. [8] This may cause large uncertainty in RUL prediction. Moreover, statistical approaches face certain challenges when dealing with high-dimensional data.

Machine learning-based approaches, on the other hand, directly map the nonlinear relationship between the input data and the corresponding RUL without establishing a degradation function. The machine learning-based method can effectively reduce the uncertainty in remaining life estimation. Besides, machine learning-based approaches have particular advantages in dealing with high-dimensional data and extracting nonlinear patterns in RUL prediction. For example, Yang et al. proposed a deep convolutional neural network (CNN) to map raw bearing vibration signals for RUL prediction. [9] Deutsch and He. presented a deep belief network (DBN) model to extract features from vibration data and then for RUL prediction. [10] Mao et al. utilized a denoising autoencoder with an elastic net and a least squares support vector machine for bearing RUL prediction. It is worth noting that both CNN and DBN are traditional feedforward (forward-feeding) neural networks. Their topology is directed acyclic structures. That is, information can only be propagated between adjacent layers rather than shared within the same layer. Moreover, the feedforward topology structure has limitations in analyzing time series data (e.g., lifetime data) because historical information is not considered in their networks. Therefore, a gated recurrent unit (GRU), which is a strengthened recurrent neural network (RNN), is introduced for RUL prediction using self-feedback neurons. [11] For example, Wang et al. proposed a quantum-weighted GRU to study the degradation process of bearings. [12]

3. Introduction to the Intended Equipment: Ship Unloader

Fig 1: of a grain suction machine unloading cargo from a ship

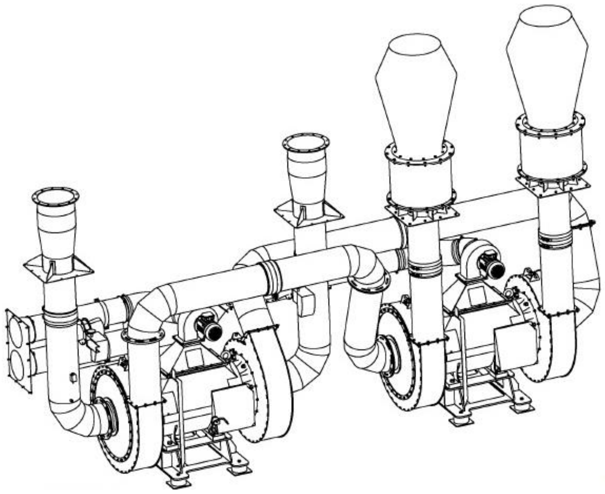

Fig 2: blower package

Fig 3: Blower Engine

A ship unloader is a complex machine with several key components that work together to unload different types of dry bulk cargo from ships to the shore. The main components of a ship unloader are: 1) Crane Traveling Mechanism to allow the unloader to move along the dock to position itself correctly with respect to the ship, 2) Trolley Traction Mechanism: to move the unloading arm or head across the ship's hold to reach the bulk material, 3) Coal Hopper and Feeding System for collecting the unloaded material and feeding them into the conveyor system for further transportation, 4) Pitching Mechanism to adjust the angle of the unloading arm or head to reach different parts of the ship's hold, 5) Lifting/Closing Mechanism: to lift and lowering the unloading arm or head, 6) Electrical and Control System for controlling all the operations of the ship unloader, ensuring efficient and safe unloading, 7) Sprinkler Dust Removal System: This system minimizes dust generation during unloading, reducing environmental impact and improving working conditions and 8) Lubrication System.

Current research focus on predicting the remaining useful life as well modeling the failure process of the blower electric motor. Here some key technical point will be proposed to follow successful researches.

Health Indicators of Blower Electric Motor:

- Temperature (winding, bearings, and vibration)

Effect of Temperature:

- Temperature rise: Indicates problems in the environment or inside the motor
- Monitoring temperature at different points: Provides important information about motor performance and health

Effect of Temperature on Winding:

- As temperature rises, electrical resistance increases, leading to a higher voltage drop and, consequently, greater power dissipation, which results in increased heat loss and decreased electrical efficiency."
- Decrease in electrical efficiency: Increase in heat loss and decrease in efficiency
- Reduction in mechanical life: Damage to bearings and other parts
- Deterioration of insulation: Risk of short circuit and serious problems

Reliability Modeling Based on Winding Temperature:

- Governing equations of heat transfer
- Electrical equations
- Prediction of temperature changes

Effect of Temperature on Bearings:

- Reduced lubrication: Increased friction and heat
- Shortened useful life: Early bearing failure
- Change in material properties: Reduced strength and hardness

Reliability Modeling Based on Bearing Temperature:

- Formulas related to temperature and thermal factors
- Probability of failure
- Probability of survival
- Probability density function (PDF)
- Cumulative distribution function (CDF)
- Temperature sensitivity parameter (β)

Effect of Vibration:

- Damage to bearings: Reduced useful life and impaired performance
- Reduced efficiency and productivity: Increased energy loss
- Damage to pipes and mechanical parts: Failure of auxiliary equipment
- Increased vibration in other equipment: Damage to surrounding structures
- Increased noise: Health and environmental issues

Reliability Modeling Based on Vibration Data:

- Statistical models
- Signal processing models
- Machine learning models
- Time-series analysis
- Image analysis techniques

Relationship between Vibration Data and Motor Failure:

- Frequency changes
- Increased vibration intensity
- Changes in time patterns
- Specific frequency parameters
- Waveform analysis
- Detection of uneven vibration

Vibration Indicators:

- Root mean square (RMS) acceleration
- Dominant frequency
- Vibration intensity
- Phase
- Peak acceleration
- Vibration power
- Crest factor
- Acceleration envelope
- Angular vibration
- Vibration vector sum
- RMS amplitude of interfering vibration
- Vibration time history

4. The Proposed Research Methodology

In this research, an innovative data-driven AI approach is introduced for more accurate prediction of the remaining useful life (RUL) of ship grain unloader electric motors. By leveraging Long Short-Term Memory (LSTM) recurrent neural networks, complex and hidden patterns within the performance data of ship grain unloader electric motors are identified and modeled, which have been less considered in traditional methods.

In this study, we introduce a novel approach for predicting the remaining useful life (RUL) of industrial equipment based on Long Short-Term Memory (LSTM) neural networks. LSTMs, due to their ability to learn complex temporal patterns and retain past information, are powerful tools for forecasting time series such as equipment degradation.

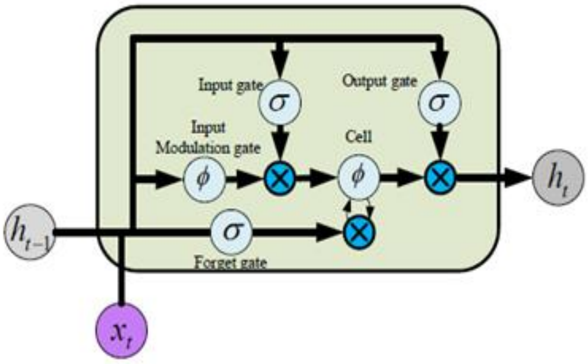

Fig 4: structure of LSTM Network

Given the innovative nature of this method and the need for extensive and specialized data in the maritime and port sectors, we initially focused on the theoretical development and evaluation of the method. This theoretical evaluation involved an extensive literature review on the application of LSTMs in equipment failure prediction, sensitivity analysis of model parameters, and adaptation of the model to synthetic data.

Our theoretical studies have shown that:

•The proposed LSTM model has a high potential for identifying complex degradation patterns in time-series data.

•Selecting an appropriate architecture for the LSTM network and fine-tuning its parameters plays a crucial role in prediction accuracy.

•By using synthetic data with characteristics similar to real-world data, the model's performance can be evaluated under various conditions.

The general principles of the proposed method are as follows:

- **Data Collection**: Initially, data related to the equipment's health status (such as bearing temperature, winding temperature, vibration, power, and rpm) is collected at regular intervals. For this research, we intend to use real-time data from a NEUERO grain unloading suction system, which is currently being collected and is shown in the figure 5.

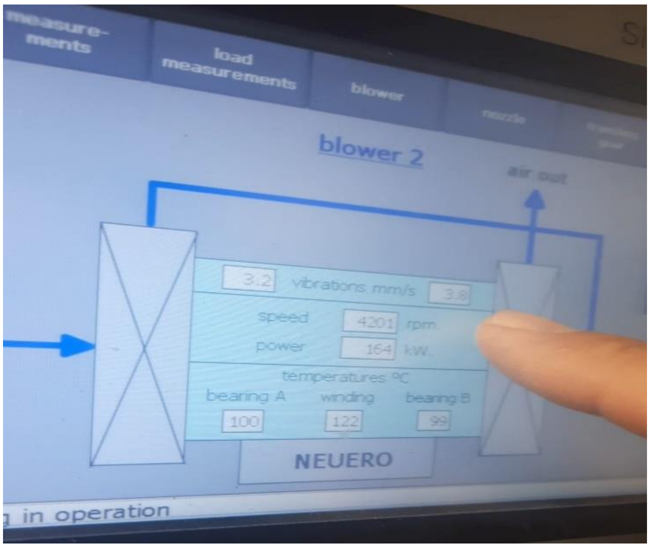

Fig 5: Monitoring the Data Collection System of the Blower Motor Sensor in Operational Conditions

- **Data Preprocessing**: The collected data is preprocessed to remove noise and extract features suitable for the model.
- **LSTM Model Construction**: An LSTM neural network with a suitable architecture for time series forecasting is designed.
- **Model Training**: The LSTM model is trained using training data to learn equipment degradation patterns.
- **Remaining Useful Life Prediction:** The trained model is used to predict the remaining useful life of new equipment.

In the next phase, we are collecting field data from a grain unloading suction system on a ship in Khuzestan province. This data will allow us to evaluate the proposed method in a real-world environment and compare its results with those of the theoretical studies. The complete results of this research will be presented in a separate paper.

We believe that presenting this method initially can help the scientific community become familiar with this innovative approach and pave the way for future research. Furthermore, we are confident that the complete results of this research, after collecting data and fully evaluating the method, will confirm that this method is a powerful tool for improving maintenance and repair management of industrial equipment.

The primary innovations of this research include:

- **Development of a customized LSTM model:** Design and implementation of a tailored LSTM model with an optimized architecture for predicting the RUL of blowers, considering the specific characteristics of the data.

- **Introduction of advanced data preprocessing techniques:** Application of time series data preprocessing techniques to enhance data quality and improve model accuracy, including noise reduction, feature extraction, and data normalization.
- **Introduction of a comprehensive model performance evaluation method:** Accurate evaluation of model performance using various evaluation metrics and comparison of results with traditional methods and other machine learning models to demonstrate the superiority of the proposed method.
- **Development of a unified framework for prediction:** Creation of a unified framework for data collection, preprocessing, model training, evaluation, and inference, which can be used as a practical tool for port and marine equipment.

The current research represents a significant step towards improving the reliability and increasing the lifespan of port and marine equipment, reducing maintenance and repair costs, and enhancing the safety of port and marine operations.

4.1 Research Steps:

4.1.1 Data Collection:

- Collecting data related to blower Engine performance, including:

Temperature / Vibration / power / Current / Speed

Table 1: Sample Data Collection

	VIB 1 (mms)	VIB 2 (mms)	Speed (RPM)	Power (KW)	Bearing Temp A (C)	Bearing Temp B (C)	Winding Temp (C)
1	3.3	3.3	4202	160	100	99	122
2	3.3	3.3	4201	158	99	99	121
3	3.3	3.3	4200	159	99	100	122
4	3.1	3.5	4202	158	100	99	121
5	3.3	3.3	4201	157	99/5	99/5	121
6	3.3	3.3	4200	157	99/5	99/6	120/8
7	3.3	3.3	4200	156	99/5	99/7	120/6
	. . .	. . .	. . .	. . .	. . .	. . .	. . .

- Collecting data related to blower operating conditions, including:
  - Load type
  - Humidity
  - Temperature
  - ...
- Collecting data on past blower failures.

4.1.2 Data Preprocessing:

- Cleaning the data from noise and missing values
- Standardizing the data
- Extracting features relevant to degradation

4.1.3 Modeling with LSTM:

- Using a Long Short-Term Memory (LSTM) neural network to model the primary degradation process of the blower
- Training the LSTM model using the collected data
- Tuning the parameters of the LSTM model

4.1.4 Model Optimization:

- Using optimization algorithms, such as:
  - Genetic Algorithm
  - Random Search Algorithm
  - Particle Swarm Optimization
- To optimize the parameters of the LSTM model and improve prediction accuracy

4.1.5 Remaining Life Prediction:

- Using the trained LSTM model to predict the remaining lifespan of the blower
- Presenting the prediction results in graphs and tables

4.1.6 Evaluation model:

To assess the performance of the LSTM model, we will employ the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) metrics. RMSE provides a measure of the average magnitude of the errors, while MAE gives the average absolute error. By minimizing these metrics, we aim to achieve a model that accurately predicts the target variable.

Advantages of the Proposed Method:

- High accuracy in predicting the remaining lifespan of the blower
- Generalizability to other similar blowers
- Ability to identify factors affecting blower degradation
- Providing solutions to increase the useful life of the blower

Limitations of the Proposed Method:

- Need for sufficient data to train the LSTM model
- Complexity of the LSTM model
- Need for expertise in artificial intelligence

The method proposed in this research offers a novel approach for modeling the primary degradation process and predicting the remaining lifespan of the Neuero ship unloader blower using LSTM and optimization algorithms. This approach can greatly enhance the accuracy of predicting the blower's remaining life and optimize its maintenance.

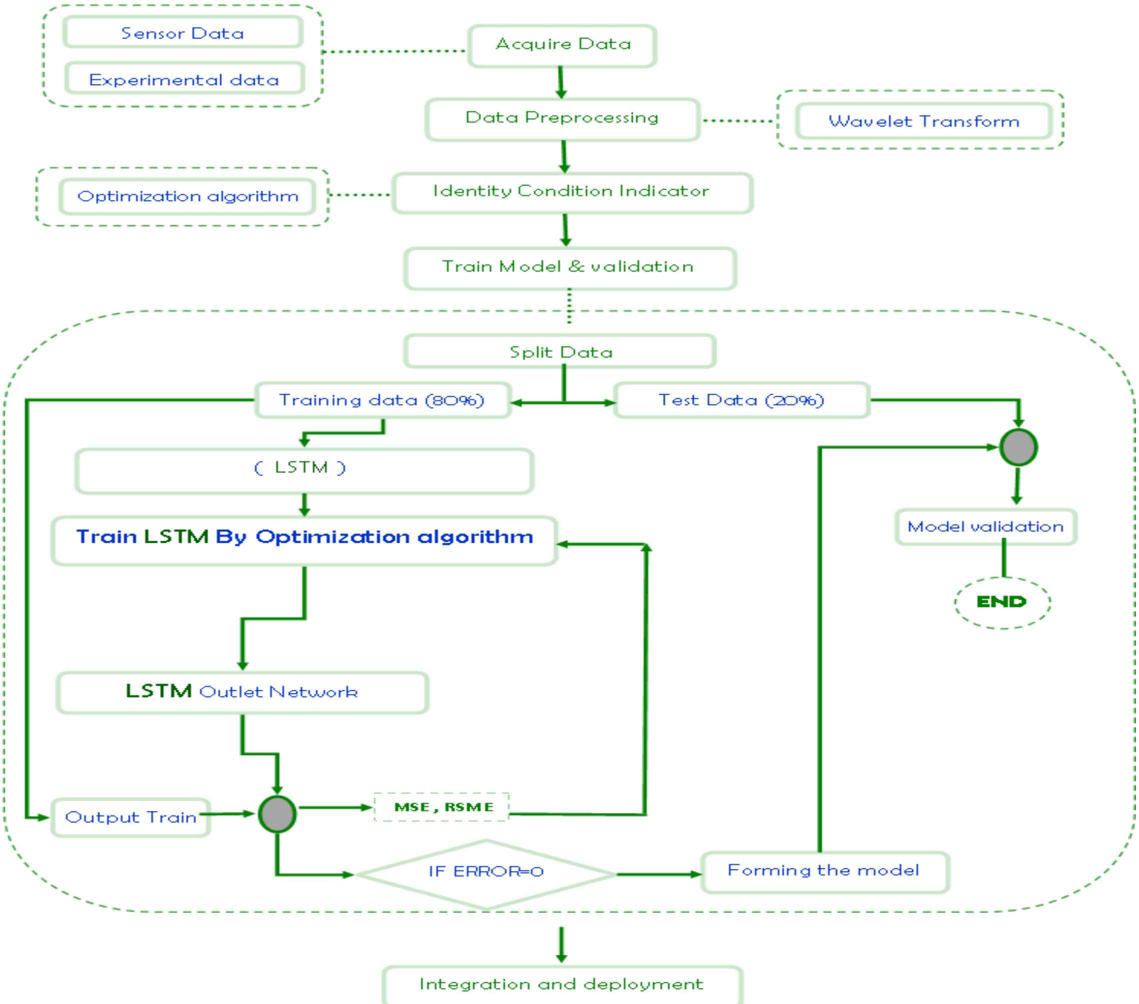

Fig (6): The proposed method is presented using a flow chart.

Notes on the Proposed Method:

- This method utilizes a Long Short-Term Memory (LSTM) neural network to model the primary degradation process of the blower.
- Optimization algorithms are employed to tune the parameters of the LSTM model and enhance prediction accuracy.
- This method can substantially contribute to improving the precision of blower remaining life prediction and optimizing its maintenance procedures.

5.Results and Discussion

This study explored the effectiveness of using data-driven and AI approaches to improve electric motor condition monitoring and failure prediction in the ports and shipping industry of Khuzestan Province, Iran. The core methodology involved leveraging deep learning algorithms, particularly the LSTM model, to meticulously analyze sensor data and predict potential motor failures.

The analysis yielded promising results, demonstrating that the proposed deep learning models possess a remarkable capability to identify progressive motor failure patterns with a high degree of accuracy. This signifies the potential of these models to empower managers and engineers within the industry to make proactive decisions regarding maintenance and upkeep of valuable equipment. Consequently, this proactive approach can lead to:

- **Reduced downtime:** By effectively predicting potential failures, corrective actions can be implemented preemptively, minimizing equipment downtime and operational disruptions.

- **Enhanced maintenance efficiency:** The ability to anticipate failures enables maintenance efforts to be targeted towards components exhibiting signs of deterioration, optimizing resource allocation and maintenance effectiveness.
- **Improved safety and reliability:** Early detection of potential failures helps prevent catastrophic events and ensures the smooth and reliable operation of critical equipment within the ports and shipping industry.

5.1 Discussion:

The findings of this research hold significant implications for the ports and shipping industry, particularly considering the crucial role of electric motors in various critical operations. The ability to accurately predict failures translates to:

- **Economic benefits:** By minimizing downtime and optimizing maintenance practices, the proposed approach can contribute to substantial cost savings for the industry.
- **Safety improvements:** Proactive maintenance and failure prevention measures can significantly enhance operational safety within ports and shipping activities.
- **Environmental considerations:** Early detection and rectification of potential failures can help minimize the risk of environmental pollution from equipment malfunctions.

It is important to note that while this study demonstrates the effectiveness of the proposed approach, certain limitations are acknowledged. The research primarily focused on data from a specific region in Iran. Future investigations using data from diverse geographical locations and a wider range of motor types would enhance the generalizability of the findings. Additionally, integrating other AI algorithms and sensor data sources could lead to more robust and comprehensive failure prediction models.

6. Research Proposals

6.1.1 Further research on the lifetime prediction of electric blower motors using predictive methods:

- Investigating and comparing different predictive methods, such as:
  - Linear regression
  - Random forest
  - Artificial neural networks
  - Deep learning
- Selecting the appropriate method based on accuracy, complexity, and practical requirements
- Optimizing predictive methods to improve accuracy and efficiency

6.1.2 Developing AI models by integrating temperature, vibration, and diverse environmental condition data:

- Collecting more data from electric blower motors under various conditions
- Extracting relevant features from the data
- Developing AI models using machine learning and deep learning algorithms
- Evaluating the performance of the models and selecting the suitable model

6.1.3 Implementing research results in real-world port and maritime environments to improve equipment maintenance:

- Collaborating with ports and maritime organizations to implement predictive models
- Developing software for easy use of the models
- Evaluating and improving the models based on practical experiences

6.1.4 Increasing the flexibility of the model to changes in various environmental conditions:

- Developing adaptive models that can adapt to new conditions
- Utilizing reinforcement learning methods to train models in real-world environments
- Optimizing models for efficiency under different conditions

6.1.5 Collaborating with the industry and relevant organizations for the operational implementation of this model on a large scale:

- Seeking financial and technical support from the industry and relevant organizations
- Establishing a consortium to develop and promote the use of models

By conducting this research, it is possible to significantly contribute to increasing the useful life of electric blower motors, reducing maintenance costs, and improving the safety and efficiency of ports and the maritime sector.

7. Conclusions

In conclusion, this research successfully demonstrated the potential of data-driven and AI approaches, particularly deep learning models, for enhancing electric motor condition monitoring and failure prediction within the ports and shipping industry. The findings highlight the benefits of this approach, including reduced downtime, enhanced maintenance efficiency, improved safety and reliability, and economic advantages. Future research should focus on expanding the study's scope by incorporating data from various regions and motor types and exploring the integration of additional AI algorithms and sensor data sources to further refine and strengthen failure prediction capabilities. By continuously advancing these methodologies, the ports and shipping industry can achieve significant improvements in operational efficiency, safety, and cost-effectiveness. This research serves as a foundation for further investigations into optimizing maintenance processes and electric motor asset management in the ports and shipping industry.

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