LSTM-BASED MACHINE LEARNING FOR REMAINING USEFUL LIFE PREDICTION OF BEARING MOTORS USING MULTI-SENSOR MONITORING

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Abstrak: Studi ini menyajikan kerangka kerja pembelajaran mesin Long Short-Term Memory (LSTM) canggih untuk memprediksi Remaining Useful Life (RUL) atau Sisa Umur Manfaat pada bantalan motor melalui pemantauan multi-sensor. Parameter-parameter kritis, termasuk getaran (Root Mean Square/RMS), emisi akustik, suhu, arus stator, dan kecepatan rotasi (RPM), disimulasikan selama periode operasional 1000 hari untuk tiga motor dengan kondisi yang bervariasi. Ambang batas kegagalan ditentukan untuk merepresentasikan kondisi operasional yang parah. Model LSTM mencapai nilai RMSE (Root Mean Square Error) sebesar 28,15, 30,29, dan 29,21 hari, serta nilai R^2 sebesar 0,989, 0,9876, dan 0,9877 masing-masing untuk dataset pelatihan, validasi, dan pengujian. Hasil ini menunjukkan akurasi prediktif dan keandalan yang tinggi. Integrasi data multi-sensor meningkatkan ketahanan (robustness) model dan mendukung perencanaan pemeliharaan proaktif. Studi ini memberikan landasan untuk integrasi di masa mendatang antara model prediktif berbasis LSTM dengan sistem pemantauan real-time yang mendukung IoT (Internet of Things) dalam aplikasi industri.

Abstract: *This study presents an advanced Long Short-Term Memory (LSTM) machine learning framework for predicting the Remaining Useful Life (RUL) of bearing motors through multi-sensor monitoring. Critical parameters, including vibration (RMS), acoustic emission, temperature, stator current, and rotational speed (RPM), were simulated over a 1000-day operational period for three motors with varying conditions. Failure thresholds were defined to represent severe operational conditions. The LSTM model achieved RMSE values of 28.15, 30.29, and 29.21 days and R^2 values of 0.989, 0.9876, and 0.9877 for training, validation, and test datasets, respectively. These results demonstrate high predictive accuracy and reliability. Integrating multi-sensor data improves the model's robustness and supports proactive maintenance planning. The study provides a foundation for future integration of LSTM-based predictive models with IoT-enabled real-time monitoring systems in industrial applications.*

1. INTRODUCTION

Industrial machinery, particularly rotating equipment like bearing motors, is critical to production reliability and operational safety [1], [2]. Bearing failures are among the most frequent causes of unplanned downtime in industrial systems, leading to significant financial losses [3], [4]. Predictive maintenance (PdM) has emerged as a proactive strategy to anticipate equipment failures before they occur, leveraging real-time condition monitoring and data-driven models [5]. Unlike traditional time-based maintenance, PdM relies on machine learning algorithms to detect patterns in operational data, which enables maintenance only when necessary and thus reduces downtime and costs. Among machine learning approaches, Long Short-Term Memory (LSTM) networks are particularly suited for modeling time-dependent degradation because they can capture long-term dependencies in sequential data [6], [7] .The choice of machine learning algorithm plays a pivotal role in determining the accuracy and effectiveness of predictive models, a factor that is equally critical when addressing challenges in predictive maintenance[8]. LSTM networks have been successfully applied in predictive maintenance for applications including electrochemical systems, wind turbines, and industrial motors [9], [10]. However, there is a research gap in applying LSTM for multi-sensor RUL prediction in bearing motors under complex operational conditions, particularly when integrating vibration, acoustic, thermal, and electrical data streams.

This study addresses this gap by developing a multi-sensor LSTM model to predict RUL in bearing motors. The model utilizes vibration (RMS), acoustic emission, temperature, stator current, and RPM data from simulated 1000-day operations across three motors with varying conditions. Failure thresholds for each parameter are defined to identify severe degradation. This research aims to demonstrate that multi-sensor LSTM modeling can provide accurate RUL predictions and offer a foundation for real-time IoT-enabled PdM systems.

Condition-based monitoring and predictive maintenance have increasingly relied on data-driven approaches, including artificial intelligence and deep learning models. Traditional threshold-based systems often fail to detect complex degradation patterns, especially when multiple parameters interact nonlinearly [2]. LSTM networks, with their ability to retain information over long sequences, have become a preferred choice for RUL prediction in machinery with time-dependent degradation behaviors [9], [11].

Several studies highlight the benefits of multi-sensor integration. For instance, vibration analysis alone may not fully capture mechanical wear, while combining thermal, acoustic, and electrical signals enhances model accuracy . Xu et al. (2025) successfully applied CNN-LSTM models for PEM water electrolyzer degradation prediction, demonstrating the capacity of LSTM networks to model complex electrochemical dynamics [12]. Similarly, Imani, Beikmohammadi, and Arabnia (2025) [13] showed that ensemble learning and multi-feature input improved classification accuracy in imbalanced datasets. Despite these advances, few studies have explored LSTM-based RUL prediction for bearing motors with integrated multi-sensor data under extended operational simulations. This study fills this gap by combining multiple sensor signals and assessing the LSTM model's ability to generalize across varying motor conditions.

2. METHODE

1. Dataset and Sensor Monitoring

The study employs a simulated dataset representing 1000 days of bearing motor operation. Figure 1 shows the specification of bearing motor, with consist of 0,75W Power and Rated speed 1797.

Figure 1. Bearing Motor Specification

Three motors with differing operational conditions were modeled to capture variability. Five key parameters were monitored:

1. Vibration (RMS) – mm/s
2. Acoustic Emission – dB
3. Temperature – °C
4. Stator Current – Ampere
5. Rotational Speed (RPM) – revolutions per minute

Failure thresholds were defined based on severe operational limits: vibration >6.3 mm/s, acoustic emission >60 dB, temperature >80°C, stator current deviation >20%, and RPM deviation >5%. These thresholds were derived from industrial standards and prior studies on motor degradation (Mobley, 2002; Jardine et al., 2006) [14], [15].

2. *LSTM Model Architecture*

The Figure 2 shows Architecture of LSTM model consisted of multiple layers of LSTM units with dropout regularization to prevent overfitting. The input comprised time-series sequences from the five monitored parameters. The model predicted the RUL in days, optimized using Mean Squared Error (MSE) loss. Hyperparameters, including the number of layers, hidden units, and learning rate, were tuned via grid search.

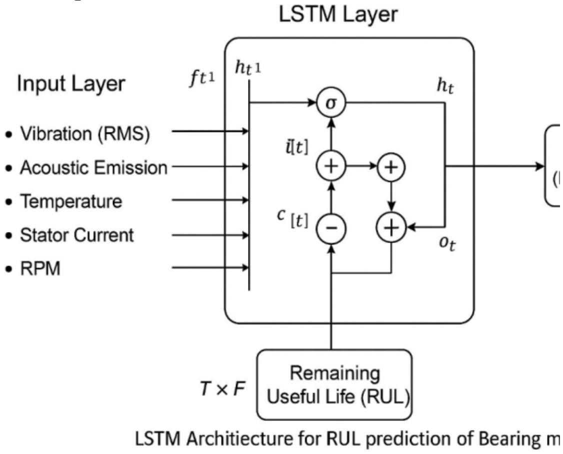

Figure 2. LSTM Architecture [16]

Training, Validation, and Testing

The dataset was split into training (70%), validation (15%), and testing (15%) sets. Model performance was evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 metrics. The LSTM model demonstrated strong generalization, with minimal performance drop between training and testing datasets.

LSTM Architecture for RUL Prediction

Long Short-Term Memory (LSTM) networks are a specialized type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. In the context of Remaining Useful Life (RUL) prediction for bearing motors, LSTM networks are particularly suitable because they can model temporal correlations in multi-sensor time-series data, such as vibration, acoustic emission, temperature, stator current, and rotational speed [17] . The Figure 3 shows an architecture of the LSTM model, which consists of an input layer that receives time-series sensor readings, followed by one or more LSTM layers that extract temporal features and dependencies. These layers are typically followed by fully connected (dense) layers that map the learned features to the predicted RUL. The output layer provides a continuous RUL estimation for each bearing motor.

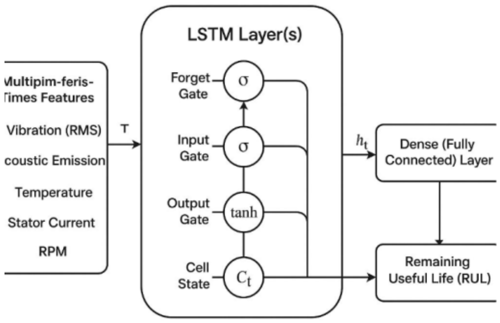

Figure 3. LSTM Architecture for RUL Prediction

3. RESULT AND DISCUSSION

Table 1 show that the LSTM model can accurately predict RUL, with RMSE values indicating low deviation between predicted and actual values. High R^2 values demonstrate that the model explains the majority of variance in the RUL data. These findings align with previous studies that highlight the effectiveness of LSTM for time-dependent degradation prediction.

Table 1. LSTM Metrics for Bearing Table Lifter

Dataset	RMSE	MAE	R^2
Train	28.15	22.89	0.989
Validation	30.29	24.21	0.9876
Test	29.21	23.04	0.9877

And Figure 4 shows the prediction accuracy trend aligned with RUL calculation result.

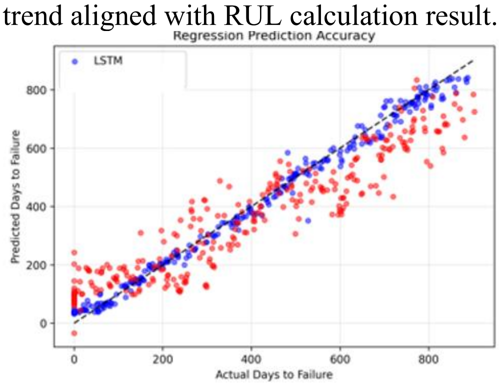

Figure 4. Regression Prediction Accuracy aligned with RUL of LSTM

I. DISCUSSION

The integration of multi-sensor monitoring data significantly enhances the predictive capability of the LSTM model. Vibration, acoustic, and thermal signals capture complementary aspects of bearing degradation, while electrical parameters like stator current and RPM provide insight into operational anomalies [18].

The model's high R^2 values across training, validation, and test datasets suggest strong robustness and minimal overfitting. Such predictive performance supports proactive maintenance strategies by allowing timely interventions before failure thresholds are reached.

4. CONCLUTION

This study demonstrates the efficacy of LSTM-based models for RUL prediction in bearing motors using multi-sensor data. The model successfully captures long-term temporal dependencies in vibration, acoustic, thermal, and electrical signals, providing accurate and reliable predictions. This framework can inform proactive maintenance scheduling, minimize unplanned downtime, and serve as a foundation for IoT-enabled real-time monitoring of industrial machinery. Future research should integrate edge computing, IoT sensor networks, and adaptive control to enhance predictive maintenance systems.

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