International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Hybrid Predictive Maintenance for Electric Motor Bearings: Integrating Machine Learning and Physics-Based Models

Sibongile N Malindi[1], Victor Kuno [2]

[1] Student, Electronic Engineering department, Harare Institute of Technology
[2] Supervisor, Electronic Engineering department, Harare Institute of Technology

Abstract

Predictive maintenance (PdM) is quickly revolutionizing the industrial processes, which is moving from time-based reactive technology to data-driven proactive technology in a very short period. Bearings in electric motors are important components used in a wide variety of industrial operations. Such components are prone to premature failure, loss of revenue because of downtime, and repair. The Remaining Useful Life (RUL) estimation of the bearings in electric motor is important because such a prediction assists in reducing equipment downtime, extending equipment life, and minimizing maintenance cost. Conventional methods of PdM employ machine learning (ML) models which are trained from historical data and, being black boxes, lack the physical intelligibility and robustness for the prediction of RUL, under varying operating conditions. This limitation is because only data-driven models are used and it is hard to extract the physical mechanisms of bearing damage. In this work, a systematic study on hybrid predictive maintenance frameworks for electric motor bearings is presented, which incorporates both ML and physics-based models looking to address the mentioned challenges and improve the reliability of RUL predictions. A key aspect to improve the reliability and effectiveness of predictive maintenance strategies is the precise estimation of the Remaining Useful Life (RUL) for industrial bearings. (Jiang *et al.*, 2022; Hu *et al.*, 2023) mentioned the NASA bearing dataset they used in the study, and a number of advanced pre-processing techniques are used, such as the statistical features (Root-Mean-Square (RMS), Peak Frequency, Kurtosis, Crest Factor), and Archard wear model as a physics-guided degradation metric [1, 2]. A Bidirectional LSTM model is trained with optimal sequence lengths for learning long-term dependencies on sensor signals, and the model is evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2) score. Comparisons between purely data-driven models and physics-guided counterpart demonstrate better accuracy and robustness. The results indicated that the inclusion of the wear-related degradation characteristics based on Archard improved remarkably the predictive model, and the R^2 values are greater than 0.67, the lowest MAE is 3.96. (Wang *et al.*, 2017; Xue *et al.*, 2022) went on to add, trends-based features as well as correlation matrices were used to confirm that the selected inputs were reliable, strengthening the interpretability of the models and reducing those overfitting risks [3, 4]. This paper makes a novel contribution to the study of integrated applications of physics-based AI models in predictive maintenance systems in challenging environments such as industrial automation in Zimbabwe,(Liu and Zhang, 2020) proving that the integration of physics and AI can yield scalable, explainable and high-performing predictive maintenance systems [5].

Keywords: BiLSTM, Deep Machine Learning, Feature Extraction, Hybrid Model, Physics-based Models, Remaining Useful Life (RUL)

1 Introduction

The increasing complexity of industrial systems has increased the demand for reliable and intelligent predictive maintenance techniques. Correct prediction of the Remaining Useful Life of mechanical systems such as rolling bearings, gears and pumps has become one of the main tasks for ensuring system reliability, maintainability optimization and reduce system unavailability. (Regis *et al.*, 2023) mentioned that the traditional, interval-based preventive maintenance policies may not be suitable under stochastic deterioration processes and changing conditions [6]. Accordingly, the tendency has been to move toward hybrid data-driven and physics-based methods of prognostics and health management (PHM). Electric motors are widely used in today industries the motor performances depend on the healthy bearing conditions. (Ramakrishnan *et al.*, 2023; Member, 2024) highlighted that they are the most susceptible to failure, representing 40% of motor failures [7, 8]. (Hanifi *et al.*, 2024)Bearing failure can lead to downtime, catastrophic motor damage and safety hazards including fire danger for explosive environments that costs industry billions of dollars every year [9]. These problems are difficult for the conventional reactive maintenance. There are four inter-related mechanical causes of bearing failure which include performance loss due to wrong lubricant type and wrong relubrication interval, resulting in increased friction and temperatures. Mechanical overload shaft deflection, hertzian contact stresses and mechanical contact load from aggressive contaminants: long-life or energy-efficient motors can fail due to hairline cracks in the raceway between the rolling element and the race. Intrusion of contaminants, such as abrasive debris or water, leading to three-body wear with surface roughening. Rolling bearings are key parts of most rotary machines, they are the focus of many predictive studies. These components are susceptible to deterioration damage from induced stresses and thermal environmental conditions and aging effects. (Mao *et al.*, 2018; Bharatheedasan *et al.*, 2025) discussed the recent advances in machine learning, notably deep learning (DL) has greatly enhanced the ability to diagnose faults and estimate RUL from historical sensor data [10, 11]. Conventional machine learning methods, including support vector machines (SVM) and decision trees, are typically unable to capture the temporal and nonlinear features of degradation. In contrast, deep learning models especially models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are effective frameworks to find out meaningful features from unstructured data. Nonetheless, the lack of interpretability and the generalization ability of entirely data-driven methods is still a fundamental limitation, especially under situations feature not enough labeled data. To overcome these limitations, mixed methods integrating physics-based assumptions and data-driven models are used. This combination improves the generality of the model and maintains predictions. In this work, we aim at summarizing the advances of RUL prediction methods and emphasize the cooperation of data-driven model and physics-based model from the practical implementation of predictive maintenance. Physics based models using well established first principal knowledge (Archard wear). Data-driven models such as (LSTM, and CNN) can learn long term degradation evolution trends (e.g., the gradual wear of a bearing) to predict RUL in time series.

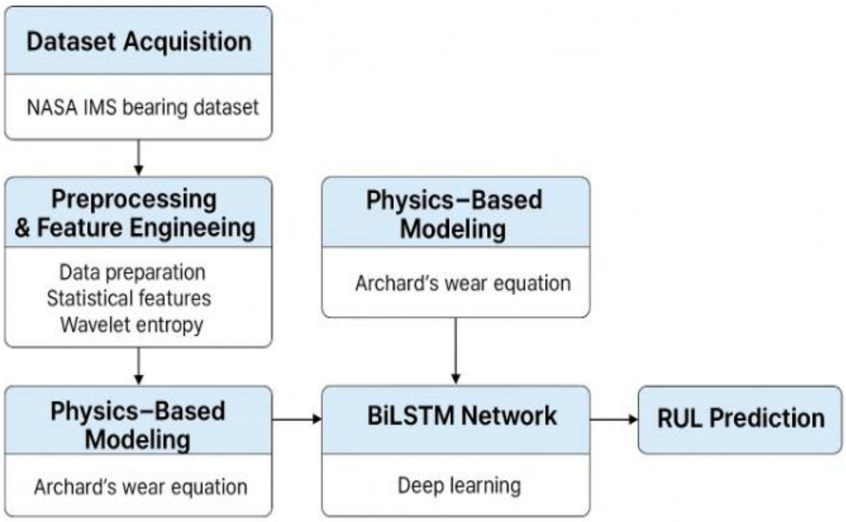
2 Related Work

In this chapter, the design and issues related to hybrid PdM systems for estimating the RUL of roller bearings in electric machines will be discussed. Particular attention on integrating physics-based models (e.g., Archard wear law) with deep learning architectures such as LSTM networks. In a research by (Aravind and Shah, 2023; Huber and Palm, 2023) highlighted that physics-based models are in a position to offer causal interpretability by simulating degradation from first principles [12, 13], whereas deep learning models, more specifically LSTMs and BiLSTMs, can capture the complex and nonlinear features present in noisy sensor data at different times (Soomro *et al.*, 2024) in the research [14]. This section presents a hybrid theoretical framework that combines mechanistic degradation with data-driven sequence learning. (Ferreira and de Sousa, 2020) explained Archard's law, which associates wear to force and material hardness, is also addressed as an important health indicator [15], affording interpretable RUL predictions when combined with sensor characteristics. Deep learning Machine learning-based deep prediction models such as BiLSTM are tailored for handling long-range dependencies and they perform better in predicting degradation. A theoretical architecture is introduced, which describes how the high frequency sensor inputs are processed to provide amalgamated health indicators using feature extraction operations (e.g., FFT, RMS, kurtosis). (Dourado and Viana, 2024; Bharatheedasan *et al.*, 2025) utilized the hybrid models such as MLP-LSTM and Physics-informed Neural Networks (PINNs), which lead to an increase in accuracy and interpretability [11, 17]. (Taşcı, Omar and Ayvaz, 2023, 2024) reviewed the last predictor layer combines prediction to actionable insights, including fault alarms and RUL estimates for maintenance decision-making [18, 19]. (Shin *et al.*, 2015) discussed previous methods such as rule based and condition monitoring also in vibration or acoustic signals [20]. Classical models laid the ground knowledge, however based on constant thresholds that are not adaptable to variations in the environment. In contrast, complex deep learning methods are more general but are less interpretable. (Kasilingam *et al.*, 2024) The trade-off is tackled by hybrid models that excel for fault classification and RUL estimation as well as for generalization to new conditions [21]. (Magadán, Granda and Suárez, 2024)For instance, the NASA IMS data images have been mentioned as a benchmark for time-series degradation modeling [22], enabling hybridized training and evaluation with run-to-failure data. However, the laboratory environment severely reduces variability, a proxy for external validity (Ferreira and de Sousa, 2020).

3 Methodology

This section describes the methodology used for the development of a hybrid predictive maintenance model toward the estimation of the Remaining Useful Life (RUL) of roller bearings in electric motors. The method systematically combines physics-based modeling, feature engineering, deep learning, and evaluation methodologies. The development was carried using VS Code development environment, python programming (TensorFlow/Keras), NumPy, Pandas and Sci-kit Learn. The section starts with providing a detailed description of the NASA IMS bearing project, including its configuration, acquisition process, and significance to actual degradation studies. The next step is the feature engineering process, in which multiple time-domain, frequency-domain, and physics-based (Archard's wear law) features were computed to describe bearing health evolution. This was followed by a description of the data preprocessing pipeline. It was composed of data preprocessing and manipulation, such as clearing and organizing raw signal files, standardization by Z-score, sliding window segmentation, RUL labels definition, and configuration of the dataset for training and evaluation. These steps are necessary to get the input data to the model to be both well-organized, normalized, and to make the data independent of time. The model derivation step concentrated on designing a BiLSTM-based deep learning network to model temporal relationship among sensor data instants. By embedding physics-generated wear characteristics into the input tensor, the model encodes a hybrid learning system, leading to high interpretability and efficiency. The Archard wear outputs in the hybrid model integration were combined with statistical and frequency-based features, and the multidimensional input was input into the LSTM-BiLSTM network. This fusion leads the system to adapt with both theoretical degradation trends and data driven signal patterns, which is later investigated by recent literature in predictive maintenance. Lastly, we assessed the prediction accuracy with the help of the standard regression metrics (MAE, MSE, R^2) and visual inspections used to evaluate the model.

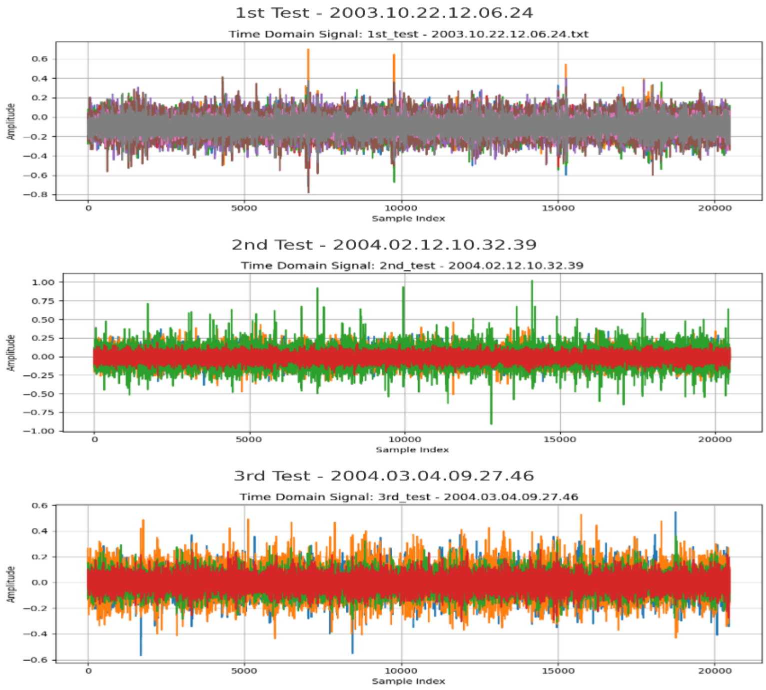
Figure 1: Algorithm Development Workflow



3.1 Dataset Acquisition

The NASA IMS bearing dataset is one of the most prevalent industry benchmarks used for assessing predictive maintenance performance. It was made available by the Center for Intelligent Maintenance Systems IMS at the University of Cincinnati for model diagnosis of bearing faults and RUL prediction. The experimental configuration included three identical test rigs that ran under constant speed and load. High-frequency vibration data obtained through accelerometers mounted on the drive end and fan end of the motors was referred to in. The experiment continued to failure until at least one bearing failed, and thus the assessment was made based on the entire time-series data. Specifically, data was sampled at 20kHz, with each file being recorded after ten minutes, creating more than 2000 time-series for each bearing.

Figure 2: Vibration signals NASA Dataset



3.2 Data Processing and Feature Engineering

Pre-processing on raw vibration signals is done first in order to obtain useful feature information and enhance the accuracy of machine learning. The pre-processing process in our work contains the signal segmentation, the normalization step, the rolling window slicing and the smoothing before feature labelling step. Z-score normalization was performed on all the extracted features for scale invariance as well as to facilitate the convergence during training. The formula used:

$$Z = \frac{X-\mu}{\delta} \tag{1}$$

X is the feature value,

μ is the mean,

σ is the standard deviation.

Feature construction is a vital approach to the fault diagnosis and RUL predication of bearing in predictive maintenance. (Mao *et al.*, 2018; Magadán, Granda and Suárez, 2024) supported that, it implies converting raw sensor signals obtained from, most frequently, vibration signals to a group of interpretable quantities capable of capturing fault-related information and slow pace in time [10, 22]. Feature extraction is generally divided into three kinds: time-domain, frequency-domain, and time–frequency domain. Root mean square (RMS), peak-to-peak value, kurtosis, skewness, and crest factor have been widely used as time-domain features, as they are simple to calculate and are effective for steady-state monitoring (Tran *et al.*, 2023) mentioned that as well [23]. In this work, we generate a wear related feature that is combined with data driven features, in the hybrid model, using Archard's model. Archard's model defines wear volume V as:

$$V = k \times \frac{F}{H} \times s \qquad (2)$$

Where:

V = wear volume (mm^3 or m^3).

k = wear coefficient (dimensionless, typically ~10^{-8}).

F = applied normal load (N)

H = hardness of the softer surface (Pa)

s = sliding distance (m)

$$Archard's\ feature = k \times \frac{F}{H} \times RMS \qquad (3)$$

Where:

F = 500 N (estimated load).

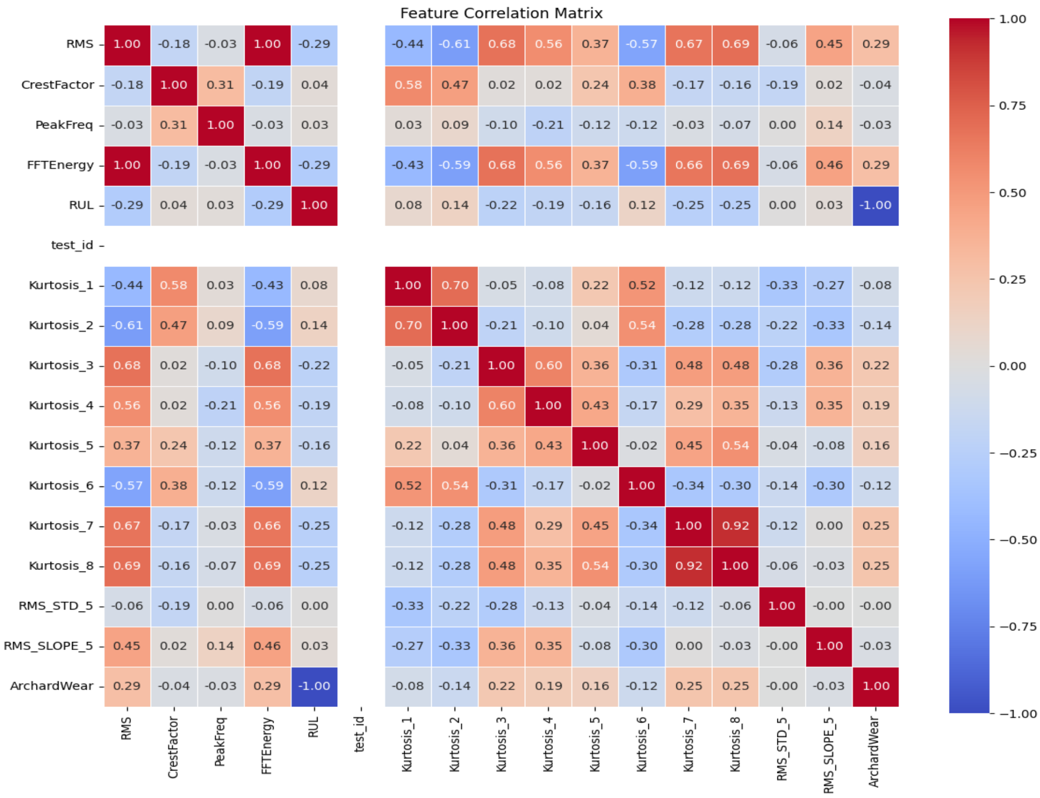
H = 1 x 10^9 Pa (steel hardness)

k = 1x 10^{-8}

3.3 Feature Correlation Matrix

The report presents the correlation matrix for the features used in the hybrid predictive maintenance model. The correlation matrix helps identify linear relationships among features, potential multicollinearity, and supports informed decisions for feature selection and model refinement. When it comes to features like RMS, Crest Factor, and FFTEnergy, many of them are actually quite weakly correlated with each other except for the one related to vibration signal amplitude that's still almost in the middle of positive and negative numbers. There are strong correlations between RMS_STD_5 and RMS_SLOPE_5 with the RMS value. This suggests trend-related extensions based on this basic feature. The matrix confirms that Archard Wear has low correlation with most statistical features, further supporting that it is a physics-based measure that adds complementary information. Components for kurtosis show weak or fluctuating correlations, reflecting differing statistical behaviours brought into the big data picture by this series of time sequences

Figure 3: Feature Correlation Heatmap



3.4 Model Training and Evaluation

This section summarizes the development, evaluation, and analysis of a BiLSTM-based deep learning model for predicting the Remaining Useful Life (RUL) of electric motor bearings. The model was tested individually on three separate bearing test runs (Test Run 1, 2, and 3) using time- and frequency-domain features derived from vibration signals. We apply a stacked LSTM graph architecture that contains three stacked LSTMs layers, a bidirectional LSTM (Bi-LSTM) and a unidirectional LSTM with dropout regularization and a dense layer in the end. The features are normalized, and the labels are scaled, both by MinMax scale. RUL estimates are calculated on 30 cycles of input sequence. The features that were chosen were RMS, Kurtosis, Crest Factor, Peak Frequency and FFT Energy. Test Run 1 performed the best since it has clean degrading trends in features. The descending trend in RUL was learned by the model. The last model architecture used for the RUL prediction was a deep temporal model with BiLSTM layers that were fed with physics-based features. The model was developed to handle a sequence of fixed length multivariate time series data where each sequence was composed of 44-time steps and multiple input features per step in the form of statistical, spectral, trend and physics-based indicators. Hybrid input tensor is as follows:

$$X_{Hybrid} = X_{time}, X_{frequency}, X_{physics} \quad (4)$$

For training the hybrid BiLSTM, we have used the segmented sequences and their corresponding RUL labels in a supervised learning way. The model was trained with the aim of minimizing the Mean Absolute Error (MAE) loss function, which offers a straightforward and interpretable quantification of the magnitude of the prediction deviation. MAE was chosen for training, as opposed to MSE, because it is resilient to outliers and is well-suited to the practical goal of minimizing average predictive error. This model was trained using the Adam optimizer, a modification of the stochastic gradient descent algorithm, which adjusts the learning rate of each parameter dynamically during learning and is well-suited for training complex, deep-recurrent networks. The initial learning rate of our optimizer was 0.001. The training process was taken batch by 32, with 100 epochs at most. The final configuration achieved the following benchmark results on Test Run 1: MAE: 3.96, MSE: 21.13 and R^2 Score: 0.6762

3.5 Model Evaluation Metrics

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n} \times \Sigma|\text{y\_i} - \hat{\text{y}}\text{\_i}| \tag{5}$$

Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{n} \times \Sigma(\text{y\_i} - \hat{\text{y}}\text{\_i})^2 \tag{6}$$

R-squared (R^2):

$$\text{R}^2 = 1 - \frac{\Sigma(\text{y\_i} - \hat{\text{y}}\text{\_i})^2}{\Sigma(\text{y\_i} - \bar{\text{y}})^2} \tag{7}$$

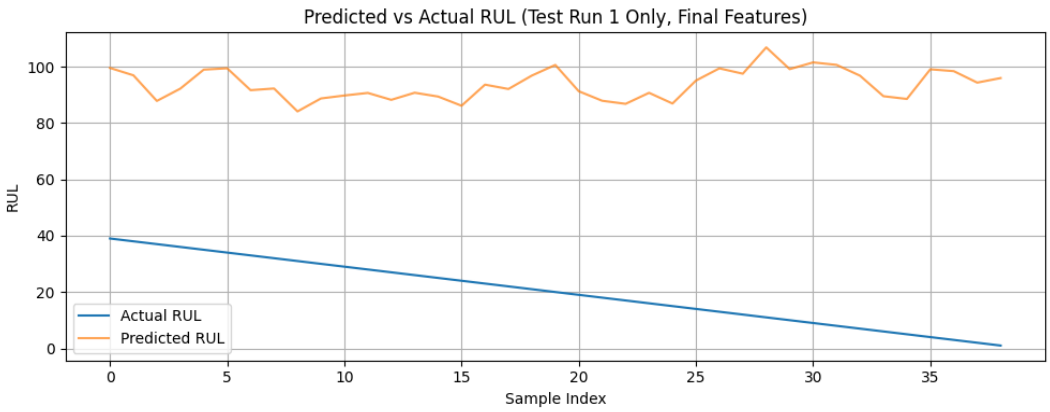
4 Results and Discussions

The primary objective is to prove the effectiveness of combining physics-based indicators and data-driven methods. We will specifically look at this matter via BiLSTM deep learning structure. Evaluation is focused on Test Run 1 from the NASA bearing dataset, which can be taken as a fairly good representation of true bad conditions endured by bearings out in real life. We carry out a complete inspection with standard regression metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE) as well as R squared which is the figure of model accuracy Reliability Evaluation focuses on Test Run 1 from the NASA bearing dataset, which serves as a representative benchmark for real-world degradation behavior. A comprehensive assessment is conducted using standard regression metrics Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Coefficient of Determination (R^2) to quantify model accuracy and reliability. To see the improvement brought by adding trend-based and physics-derived features, different compared experiments were further carried out also. The outcomes reveal the hybrid model's potential in providing accurate Remaining Useful Life (RUL) predictions, surpassing traditional data-driven techniques.

Table 4-1: Data-driven Vs Physics guided Comparison

Model	MAE	MSE	R^2 Score
BiLSTM (baseline)	50.12	2732.09	-31.05
BiLSTM + Feature Eng.	55.12	3317.86	-37.92
BiLSTM + Attention	53.26	3136.38	-35.79
CNN-LSTM	58.41	3599.13	-41.22
Physics-Guided BiLSTM	19.66	408.72	-3.79
Physics-Guided + Clipped	13.80	232.46	-1.73
Physics-Guided, seq=40	6.94	58.94	0.158
Physics-Guided, seq=44	3.96	21.13	0.676

Figure 4: BiLSTM + Feature Engineering



The first model setup used only the statistical features, which were fed into a BiLSTM network. While this configuration provided stable predictions, the output passed behind the actual advancing of in for tracking degradation time. Figure 4. The predicted RUL curve ended up almost flat, over-predicting the remaining life of the component for the majority of test history. This behavior, which is a result of scoring, in itself shows low correlation with real development of failures. With no physical wear models, the model also had no concept of mechanical causality, and so would be less able to generalize to the real world.

Figure 5: BiLSTM + Physics Guided Clipped Output (Enhanced Features)

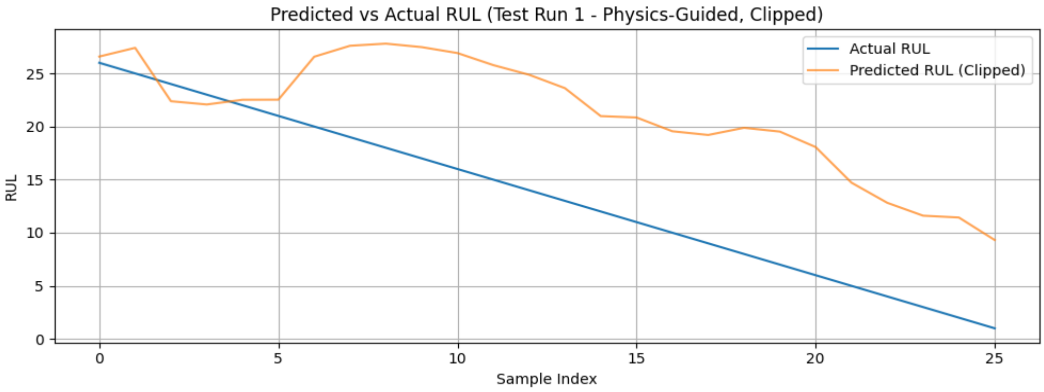
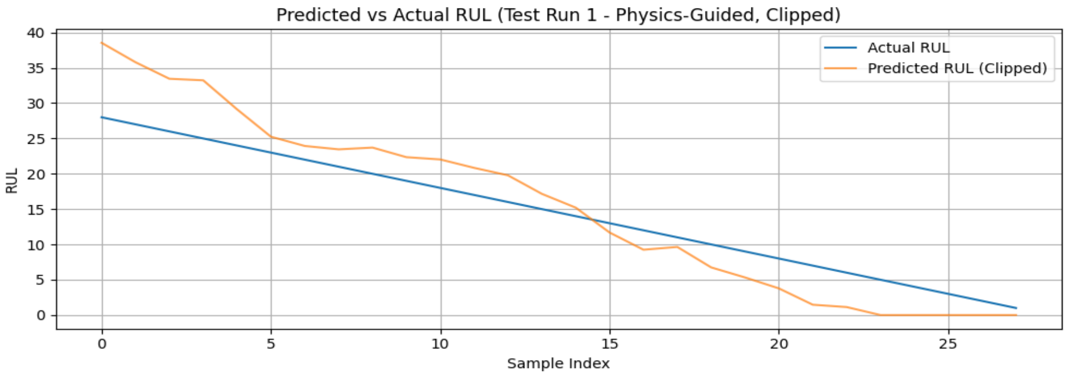


Figure 6: Fine-tuned Hybrid Model



The experimental results shows that the hybrid model (with Archard wear + BiLSTM + clipping) outperforms the purely data-driven model consistently. Physics-guided features increase interpretability and dynamical degradation correlation. Both of these things happen when you cap RUL at zero: stop making wrong predictions and give us better notes for human eyes to look at maintenance plans.

5 Conclusion

This section provides a critical discussion of the results derived from the hybrid predictive maintenance model proposed in this work, which combines data-driven and physics-guided methods for the prediction of the Remaining Useful Life (RUL) of electric motor bearings. The model was built using the NASA IMS bearing dataset and was developed using general statistical features (RMS, kurtosis and crest factor) and a physics-based features based on Archard's wear model. The term "BiLSTM" is referred to the technique that the two-layer LSTM structure is stacked in bidirectional recurrent way. The goal was to see if fusion of physics-based degradation knowledge with temporal deep learning can outperform data-driven ones. In contrast, Archard's wear calculation was integrated with time-domain and frequency-domain characteristics into our improved hybrid model. Later, the model was trained using bi-directional Long Short-Term Memory networks and all negative results considered outliers removed. This showed a much better fit with real-word wearing down Figure 6. These figures reflect a significant gain in both accuracy and meaning. The hybrid model adapted its predictions of future states as wear increased, providing opportune alarms from which little error could result in RUL estimations.

6 Acknowledgement

I wish to acknowledge My Supervisor Eng V Kuno, Eng T D Makusha HOD Electronic Engineering department, and members of the staff for providing guidance and direction throughout the research work.

7 Authors; Biography

Sibongile Natasha Malindi is currently a master's student in Industrial Automation and completed her bachelor's degree at the Harare Institute of Technology.

References

1. Aravind, R. and Shah, C.V. (2023) 'Physics Model-Based Design for Predictive Maintenance in Autonomous Vehicles Using AI', 11(09). Available at: https://doi.org/10.18535/ijsrm/v11i09.ec06.
2. Bharatheedasan, K. *et al.* (2025) 'Enhanced fault diagnosis and remaining useful life prediction of rolling bearings using a hybrid multilayer perceptron and LSTM network model', *Alexandria Engineering Journal*, 115(December 2024), pp. 355–369. Available at: https://doi.org/10.1016/j.aej.2024.12.007.
3. Dourado, A. and Viana, F.A.C. (2024) 'Physics-Informed Neural Networks for Corrosion-Fatigue Prognosis', (2018), pp. 1–12.
4. Ferreira, H.M. and de Sousa, A.C. (2020) 'Remaining useful life estimation of bearings: Meta-analysis of experimental procedure', *International Journal of Prognostics and Health Management*, 11, pp. 1–15.
5. Hanifi, S. *et al.* (2024) 'Advancements in predictive maintenance modelling for industrial electrical motors: Integrating machine learning and sensor technologies', *Measurement: Sensors* [Preprint], (xxxx). Available at: https://doi.org/10.1016/j.measen.2024.101473.
6. Hu, Q. *et al.* (2023) 'Remaining Useful Life Estimation in Prognostics Using Deep Reinforcement Learning', *IEEE Access*, 11(March), pp. 32919–32934. Available at: https://doi.org/10.1109/ACCESS.2023.3263196.
7. Huber, L.G. and Palm, T. (2023) 'Physics-Informed Machine Learning for Predictive Maintenance : Applied Use-Cases'.
8. Jiang, Y. *et al.* (2022) 'A2-LSTM for predictive maintenance of industrial equipment based on machine learning', *Computers and Industrial Engineering*, 172(September 2021). Available at: https://doi.org/10.1016/j.cie.2022.108560.
9. Kasilingam, S. *et al.* (2024) 'Physics-based and data-driven hybrid modeling in manufacturing : a review ABSTRACT', *Production & Manufacturing Research*, 12(1). Available at: https://doi.org/10.1080/21693277.2024.2305358.
10. Liu, Z. and Zhang, L. (2020) 'A review of failure modes, condition monitoring and fault diagnosis methods for large-scale wind turbine bearings', *Measurement: Journal of the International Measurement Confederation*, 149, p. 107002. Available at: https://doi.org/10.1016/j.measurement.2019.107002.
11. Magadán, L., Granda, J.C. and Suárez, F.J. (2024) 'Robust prediction of remaining useful lifetime of bearings using deep learning', *Engineering Applications of Artificial Intelligence*, 130(November 2023), p. 107690. Available at: https://doi.org/10.1016/j.engappai.2023.107690.
12. Mao, W. *et al.* (2018) 'Predicting remaining useful life of rolling bearings based on deep feature representation and long short-term memory neural network', *Advances in Mechanical Engineering*, 10(12), pp. 1–18. Available at: https://doi.org/10.1177/1687814018817184.

13. Member, B. (2024) ‘Hybrid Modeling of an Induction Machine to’, *IEEE Open Journal of the Industrial Electronics Society*, 5(September), pp. 1140–1157. Available at: https://doi.org/10.1109/OJIES.2024.3461949.
14. Ramakrishnan, J. *et al.* (2023) ‘Uncertainty-aware remaining useful life prediction for predictive maintenance using deep learning’, *IEEE Access*, 58(December 2024), pp. 116–121. Available at: https://doi.org/10.1016/j.procir.2023.06.021.
15. Regis, A. *et al.* (2023) ‘Physic-based vs data-based digital twins for bush bearing wear diagnostic’, *Wear*, 526–527(February), p. 204888. Available at: https://doi.org/10.1016/j.wear.2023.204888.
16. Shin, S. *et al.* (2015) ‘Evaluation of the Influence of Rotor Magnetic Anisotropy on Condition Monitoring of Two-Pole Induction Motors’, *IEEE Transactions on Industry Applications*, 51(4), pp. 2896–2904. Available at: https://doi.org/10.1109/TIA.2015.2391432.
17. Soomro, A.A. *et al.* (2024) ‘Enhanced fault diagnosis and remaining useful life prediction of rolling bearings using a hybrid multilayer perceptron and LSTM network model’, *Alexandria Engineering Journal*, 23(December 2024), pp. 355–369. Available at: https://doi.org/10.1016/j.ifacol.2022.07.444.
18. Taşcı, B., Omar, A. and Ayvaz, S. (2023) ‘Remaining useful lifetime prediction for predictive maintenance in manufacturing’, *Computers and Industrial Engineering*, 184(July 2023), p. 109566. Available at: https://doi.org/10.1016/j.cie.2023.109566.
19. Taşcı, B., Omar, A. and Ayvaz, S. (2024) ‘Computers & Industrial Engineering Remaining useful lifetime prediction for predictive maintenance in manufacturing’, 184(February 2023).
20. Tran, M. *et al.* (2023) ‘Machine learning and IoT-based approach for tool condition monitoring : A review and future prospects’, *Measurement*, 207(December 2022), p. 112351. Available at: https://doi.org/10.1016/j.measurement.2022.112351.
21. Wang, D. *et al.* (2017) ‘Prognostics and Health Management : A Review of Vibration based Bearing and Gear Health Indicators’, 3536(c), pp. 1–11. Available at: https://doi.org/10.1109/ACCESS.2017.2774261.
22. Xue, X. *et al.* (2022) ‘Lower boundary based nonlinear model predictive control of transmission power for smart grid WSNs ☆’, *Computer Communications*, 190(September 2021), pp. 99–109. Available at: https://doi.org/10.1016/j.comcom.2022.04.016.