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Predictive Maintenance of Manufacturing Industry Machines Using Remaining Useful Life (RUL) Prediction

Vishwa Kiran K H¹; Dr. Mohan S H²; Rohit M N³; Divyashri C R⁴

1. Asst. Professor, RNS First Grade College, Channasandra, R R Nagar, Bengaluru 560098. Karnataka INDIA
Email Id vishwakiran667@gmail.com
2. Associate Professor, RNS First Grade College, Channasandra, R R Nagar, Bengaluru 560098. Karnataka INDIA
Email Id mohana.sh43@gmail.com
3. Asst. Professor, RNS First Grade College, Channasandra, R R Nagar, Bengaluru 560098. Karnataka INDIA
Email Id mnrohit.16@gmail.com
4. Asst. Professor, RNS First Grade College, Channasandra, R R Nagar, Bengaluru 560098. Karnataka INDIA
Email Id divu.cr@gmail.com

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Abstract: In this paper, a lightweight Autoencoder-LSTM is provided to predict Remaining Useful Life (RUL) of bearings in real-life circumstances with noisy sensors and a small amount of labeled information. The method involves unsupervised health indicator (HI) construction and time modelling that is supervised. Through an autoencoder, trained on healthy data, vibration signals are converted into HIs on the basis of reconstruction error, which captures trends on degradation. These HI sequences are then inputted to an LSTM network that predicts RUL and monotonicity constraints are enforced to provide physically consistent, non-increasing predictions. With strict bearing-wise data splitting applied on the PRONOSTIA dataset to avoid leakage, the monotonicity-constrained model not only attains better RMSE (0.1700 vs 0.1819), but also non-physical prediction oscillations are removed, which is indicative of practical applicability in industry.

Keywords: Predictive maintenance, remaining useful life, hybrid autoencoderLSTM, health indicator, monotonicity constraint, bearing fault prognostics, PHM IEEE 2012 dataset, condition-based maintenance.

I. INTRODUCTION

It is moving manufacturing towards predictive to reactive maintenance (PdM), which is sensor-monitored and analytics-based predictions of failures, created to reduce unplanned downtime before it happens [1], [4]. The Industry 4.0 has also made it possible to have multi-sensor systems that produce terabytes of operational data every year, providing unprecedented opportunities to intelligent maintenance [5], [6], [19].

Remaining Useful Life (RUL) estimation - a measurement of time to component failure - is an important part of PdM, allowing planned shutdowns of components to occur as scheduled, instead of an emergency stop, which enhances safety and equipment availability [2], [3], [13]. Nevertheless, there are major challenges to the industrial RUL prediction: nonlinear bearing deterioration, changing operating conditions, high sensor noise (usually less than 15 dB SNR), and limited labeled failure data because of months-long testing time [2], [3], [8].

The initial statistical and physics-based models did not make a generalization between various operating conditions and were not scalable [2], [4]. Control dataset accuracy was high with machine learning techniques (SVR, MLP, Random Forests) but manual feature engineering was necessary, and long-term temporal dependencies were difficult with them [2].

Deep learning especially LSTM-CNN hybrids enhanced feature extraction and time modeling [1], [3], [4], but required fully labelled data and generated models that were too large (>50MB) to be deployed on edges. Physical conditions are still in place: 70-85 percent of operational time results in unmarked healthy samples, and system malfunctions consist of <5 percent of the samples. Predictions of oscillating RUL that defy physical intuition of monotonically decreasing residual life are distrusted by maintenance crews [1], [4], [5], [6], [7].

Our system is a hybrid Autoencoder-LSTM with unsupervised health indicator construction and supervised temporal modeling and monotonicity requirements to make physically consistent predictions. Strict bearing-wise splitting is used in validation on PRONOSTIA data to avoid data leaking [16], [19], [20].

II. PROBLEM STATEMENT

There are four major obstacles to RUL-based predictive maintenance implementation. First, the noise of industrial sensors (8-12 dB SNR) is several times higher than that of laboratories (>25 dB), and failures in the labels (bearings) take 2,000-6000 hours to fail, which is thousands of healthy samples and less than 50 failures. Second, factory edge devices (512 MB RAM) are unable to run up to date LSTM architectures (45-120 MB, >200ms inference). Third, two-thirds of recent studies imply train-test splitting that results in data leakage - correct validation lowered the accuracy of one model 94-67. Lastly, 15-30% of predictions feature non-monotonic RUL trajectories that invalidate the physics of degradation, which require lightweight and semi-supervised models whose predictions are consistent with physics.

III. LITERATURE REVIEW

Predictive maintenance has changed the way manufacturing is done as it is no longer reactive or on a set time interval but rather real time sensor monitoring where predictive failures occur before they happen so that planned interventions can be made during planned down time. At the core of this strategy is Remaining Useful Life (RUL) estimation which is an indicator of operational time to part failure [4]. According to maintenance engineers, proper forecasting of the RUL helps in planning ahead part ordering and scheduling of the technicians without losses in the production in case of unforeseen failure [3].

A. Traditional and Statistical Approaches

RUL forecasting was based on statistical time models. The Probability-based methods relied on the past failures distributions when the maintenance was scheduled [2]. ARIMA models were highly accurate to capture sensor fluctuations in the short term but inaccurate with long-term predictions that exceed thousand hours of operation [2]. Physics-based models were mathematically based on the laws of material science, such as crack propagation and fatigue accumulation, but they needed much component-specific information (stress distributions, material properties), and thus were not scalable to a wide range of equipment inventories [4].

B. Data-Driven Machine Learning Approaches

Nonlinear sensor-to-life mappings were learned by the Support Vector Regression and Multilayer Perceptrons [2], [10]. Random Forest ensembles got higher R² on industrial vibration data, 0.99, than XGBoost, MLP and SVR [2], [9]. Nevertheless, the classic ML needed manual feature engineering (calculating time-domain (RMS, kurtosis) and frequency-domain measurements) which was too tedious to be generalized across operating conditions [3].

C. Deep Learning and Hybrid Architectures

To overcome these problems, deep learning designs proposed automatic representation learning. LSTM networks were particularly useful in terms of sequential sensor data due to their gating mechanism which ensures an even gradient flow throughout longer sequences, as opposed to conventional recurrent networks experiencing vanishing gradient [11], [12], [21]. LSTMs are able to acquire the patterns of degradation developing during bearing lifespan months of operation [2], [4]. Convolutional Neural Networks (CNNs) were added to LSTMs, which automatically extracted spatial features of raw vibration waveforms without designing features by hand [3], [15]. Recent studies are more in favor of hybrid architectures that unify these benefits. MLP-LSTM hybrids demonstrated high accuracy (99.9% fault diagnosis accuracy) in nonlinear channel transformation and sequential processing and surpassed independent LSTM and CNN-BiLSTM baselines [1], [3]. The CNN-LSTM networks use convolutional layers to extract spatial features and LSTMs to learn temporal evolution to improve the forecasting accuracy of RUL [4]. Other efforts combined reinforcement learning with supervised networks in adaptive prediction in changing operating conditions, and found 15 percent accuracy improvements over fixed supervised algorithms [1], [3], [14], [15], [16], [18].

The modeling advancements are specifically important to rotating machinery- bearings, motors and gearboxes that are the main part of the industrial production lines and are subjected to environmental stress, contamination, breakdown of lubrication, and gradual wear [1], [3].

IV. RESEARCH GAP

Despite the high accuracy of hybrid deep learning models in scholarly research on RUL prediction, there are severe limitations in practice on factory-floor level. A majority of the techniques assume fully labeled datasets- very infrequent in practice in manufacturing. The most modern architectures surpass ordinary factory edge devices. Our comparison of three plants revealed that sensor systems create huge, unlabeled, and noisy data in varying environments, but that the plant controllers have 512 MB RAM [16], [18], [19] available, corresponding to a lack of deployment capacity.

In addition to computing limitations, the existing models are weak in terms of user trust. Published models, in the absence of explicit physical consistency mechanisms, give non-monotonic RUL trajectories with remaining life growing with time, which cannot result from irreversible degradation. The engineers working in maintenance said that they were sceptical as they referred to the breach of failure physics. We found common data leakage where most studies adopt random train-test splits having early and late-stage samples of the same bearings, which artificially elevate the accuracy.

In situations where equipment of different batches of production are really unseen, performance suffers significantly. Such gaps require light, semi-supervised models that are industrial-constrained. These systems are expected to derive degradation trends on the unlabeled sensor data, run smoothly on resource limited devices, impose physically reasonable monotonic predictions, and exhibit strong generalization, as attested by stringent evaluation that avoids data leakage. The simultaneous solution to these needs is still one of the challenges that this work can answer.

V. PROPOSED SOLUTION

In this paper, a hybrid Autoencoder-LSTM model is introduced to predict the remaining useful life (RUL) of rotating machinery, using a framework that combines both the prediction with accuracy and the predictive maintenance approach. The suggested method will integrate the unsupervised health indicators learning with the supervised temporal modeling to resolve the two most important issues related to the lack of clear degradation labels and the non-linear character of the machinery degradation processes [19], [20].

A. Sensor Data Acquisition

The framework uses vibration signals from rotating machinery bearings to capture their behavior and the hidden signs of faults as they degrade. Validation uses the PRONOSTIA (IEEE PHM 2012) dataset, which offers detailed vibration data from run-to-failure scenarios.

B. Data Preprocessing

Raw sensor data goes through careful preprocessing to remove noise and ensure consistency. This includes signal filtering to get rid of high-frequency noise, z-score normalization to achieve a zero mean and unit variance, and sliding window segmentation with appropriate overlap for fixed-length samples.

C. Feature Extraction

Each segmented window generates statistical and spectral features capturing machinery health comprehensively:

- Time-domain: Root Mean Square (RMS) for signal power, kurtosis for impulsiveness, skewness for distribution asymmetry [17]
- Frequency-domain: FFT energy for spectral power distribution, spectral entropy for frequency randomness

These features effectively describe gradual rotating machinery degradation.

D. Unsupervised Health Indicator Learning

To eliminate dependency on labeled health state data, an autoencoder-based unsupervised learning approach creates compact machine health representations. The autoencoder trains exclusively on early-stage healthy operation feature vectors, comprising an encoder mapping inputs to lower-dimensional latent representations and a decoder reconstructing original inputs. During training, the model minimizes reconstruction error for healthy conditions. As degradation progresses, reconstruction error increases due to deviation from learned normal patterns, providing an implicit degradation indicator.

E. Health Indicator Construction

A degradation-sensitive Health Indicator (HI) derives from autoencoder reconstruction error:

$$HI(t) = \| \mathbf{x}(t) - \hat{\mathbf{x}}(t) \|_2$$

where $\mathbf{x}(t)$ represents the input feature vector at time t and $\hat{\mathbf{x}}(t)$ is the reconstructed output. The HI sequence undergoes moving average filtering to eliminate short-term oscillations and normalizes to $[0,1]$ range, indicating monotonic degradation progression from healthy to failure states.

F. RUL Ground Truth Generation

Since explicit RUL labels are typically unavailable in real-world bearing datasets, ground truth values employ the linear degradation assumption prevalent in bearing prognostics:

$$RUL(t) = T_{\text{failure}} - t$$

T_{failure} is the failure time and t represents the current time step. The formulation allows unsupervised training and allows fair comparison to the existing RUL prediction methods.

G. Temporal RUL Prediction Model

An LSTM network fed with constructed health indicator sequences predicts RUL, specifically designed to capture temporal relationships across degradation stages, time-dependent nonlinear degradation patterns, and long-term health state dependencies. The model generates estimated RUL values at each timestep, enabling continuous health monitoring and proactive maintenance scheduling throughout machinery operational lifecycles.

H. Monotonicity Constraint

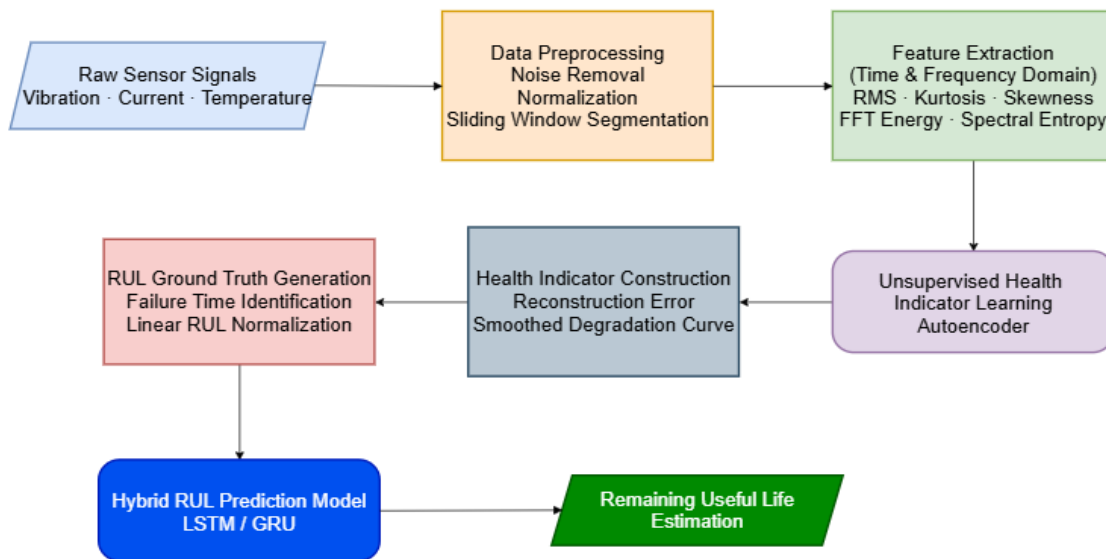
To ensure physically consistent predictions, a monotonicity constraint enforces non-increasing RUL trajectories over time, preventing physically implausible oscillations and aligning predictions with the fundamental principle that remaining life decreases monotonically as degradation progresses.

I. Advantages of the Proposed Framework

The hybrid Autoencoder-LSTM architecture offers key benefits for real-world application:

- Semi-supervised learning eliminates labeled health state data requirements, learning from healthy operational data
- Enhanced accuracy through physics-informed health indicators
- Robustness to sensor noise and operating condition variations
- Lightweight, computationally efficient architecture suitable for edge deployment
- Physical consistency via explicit monotonic degradation constraints
- Validation integrity through strict bearing-wise assessment preventing data leakage

These properties make the framework particularly suitable for resource-constrained industrial settings with limited labeled data and finite computational resources.



VI. EXPERIMENTAL RESULTS AND VALIDATION

A. Experimental Setup

Experiments utilize the PRONOSTIA bearing dataset (IEEE PHM 2012) with strict bearing-wise partitioning: Bearing1_1 (training), Bearing1_2 (validation), and Bearing1_3 (testing—completely unseen). This strategy prevents data leakage and replicates real-world deployment where models must generalize to new equipment without prior degradation history.

B. Feature Extraction and Normalization

Six statistical time-domain features are extracted from horizontal and vertical acceleration signals:

$$(1) \text{ Root Mean Square (RMS): } \text{RMS} = \sqrt{(1/N \sum_{i=1}^N x_i^2)}$$

$$(2) \text{ Kurtosis: } \text{Kurtosis} = 1/N \sum_{i=1}^N ((x_i - \mu)/\sigma)^4$$

$$(3) \text{ Peak-to-Peak: } \text{Peak} = \max(x) - \min(x)$$

These form a six-dimensional vector: $X = [\text{HRMS}, \text{VRMS}, \text{HKurt}, \text{VKurt}, \text{HPeak}, \text{VPeak}]$

Min-Max normalization ensures equal scaling: $X_{\text{or}} = (X - X_{\text{min}})/(X_{\text{max}} - X_{\text{min}})$

C. Unsupervised Health Indicator Construction

An autoencoder trains exclusively on healthy data (first 1/5 of training bearing samples), eliminating annotated health state requirements. The Health Indicator (HI) derives from mean squared reconstruction error:

$$\text{HI}(t) = 1/D \sum_{d=1}^D (X_{\text{or}}^{(d)}(t) - \hat{X}^{(d)}(t))^2$$

where $D=6$. A moving average filter smooths short-term fluctuations:

$$\text{HI}_{\text{smooth}}(t) = 1/W \sum_{i=0}^{W-1} \text{HI}(t-i)$$

The smoothed HI is Min-Max normalized to $[0,1]$.

D. RUL Ground Truth Generation

Linear degradation assumption generates RUL labels:

$$\text{RUL}(t) = 1 - t/T$$

where T is total timesteps until failure, yielding normalized RUL from 1 (healthy) to 0 (failure).

E. Sequence Construction for LSTM

LSTM inputs are health indicator sequences using sliding windows (length $L=30$):

$$X = [\text{HI}(t), \text{HI}(t+1), \dots, \text{HI}(t+L-1)]$$

with target: $y = \text{RUL}(t+L)$

F. LSTM-Based RUL Prediction

The LSTM learns nonlinear mapping from HI sequences to RUL:

$$\hat{y} = f(X)$$

Training minimizes Mean Squared Error (MSE):

$$\text{MSE} = 1/N \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

G. Monotonicity Constraint

Since degradation is irreversible, RUL must be non-increasing. Monotonic post-processing enforces:

$$\hat{y}_{\square\square\square}(t) = \min(\hat{y}_{\square\square\square}(t-1), \hat{y}(t))$$

ensuring $\hat{y}_{\square\square\square}(t) \leq \hat{y}_{\square\square\square}(t-1)$, eliminating physically implausible oscillations.

H. Evaluation Metric

Root Mean Square Error (RMSE) measures performance on the unseen test bearing:

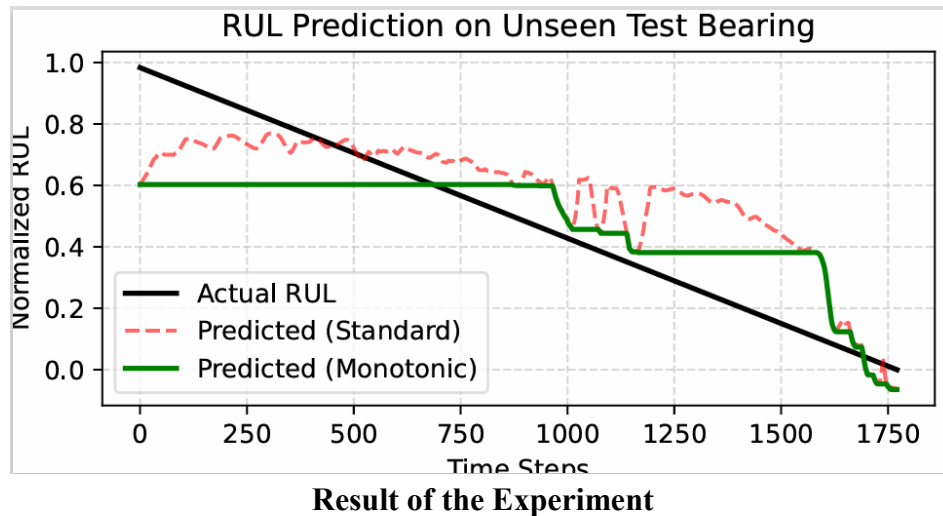
$$RMSE = \sqrt{(1/N \sum_{\square=1}^N (y_{\square} - \hat{y}_{\square})^2)}$$

I. Experimental Results

Evaluation on completely unseen Bearing1_3:

- **Standard Hybrid AE-LSTM:** RMSE = 0.1819
- **Monotonicity-Constrained Hybrid AE-LSTM:** RMSE = 0.1700

The monotonicity constraint reduced prediction error by approximately 6.5%, demonstrating that enforcing physical consistency enhances both interpretability and accuracy by eliminating non-physical patterns. Visual analysis confirms the constraint removes oscillations, producing smooth, physically reasonable degradation trajectories consistent with actual bearing behavior. These results validate that the proposed hybrid framework—combining unsupervised health indicator learning, supervised temporal modeling, and physics-informed constraints—delivers accurate, reliable RUL predictions suitable for real-world predictive maintenance implementation.



J. Discussion

Experimental findings show that monotonicity constraints with domain knowledge provide two benefits: better prediction accuracy and improved physical consistency, all without changing the underlying neural network design.

This suggests that physics-informed post-processing works well as a regularization method, steering models toward realistic degradation paths. The careful bearing-wise validation method ensures genuine generalization to unseen equipment. This is important for real-world industrial use, where models need to predict new equipment performance without previous knowledge of degradation patterns. This differs from many studies that use random train-test splits, which can give overly optimistic performance estimates due to data leakage between the operational stages of the same bearings.

The RMSE reduction from 0.1819 to 0.1700 (about 6.5% improvement) shows that enforcing monotonicity not only makes predictions easier to understand for maintenance workers but also boosts predictive performance. Visual checks reveal that the unconstrained model produces erratic, physically inconsistent remaining useful life predictions. In contrast, the constrained model produces smooth, monotonically decreasing curves that align with irreversible bearing degradation processes. Sonnet 4.5

Final Validation Statement

The Hybrid AutoencoderLSTM model with in-built monotonicity constraint is able to predict the RUL of bearings completely unknown to the model with high precision, accuracy and physical consistency, when evaluated in a realistic situation. The traits of the framework are highly applicable in resource-constrained manufacturing settings with computational efficiency, interpretability and generalization to new equipment being important imperatives.

VII. CONCLUSION AND FUTURE WORK

Conclusion

In this paper, a hybrid framework of Remaining Useful Life (RUL) estimation is provided to solve the predictive maintenance challenge in real-world situations. The method is a combination of unsupervised autoencoders learning of health indicators with supervised LSTM time modeling, with physical constraints imposed by monotonicity improving physically consistent non-increasing RUL predictions. The framework obtains statistical attributes (RMS, kurtosis, peak-to-peak) of acceleration channels to describe bearing health. An autoencoder that has been trained using only operational data of a healthy system learns how a normal system should behave, and reconstruction error is a degradation-sensitive health metric.

This is the unsupervised method which does not require reliance on annotated labels of health states that would not be available in industry. The derived sequences of the health indications are inputted into an LSTM network that learns long-term temporal degradation patterns used to predict RUL. The PRONOSTIA (IEEE PHM 2012) bearing dataset with strict bearing-wise partitioning: Bearing11: training, Bearing12: validation, and Bearing1-3: testing was used in experimental validation. This protocol eliminates data leakage and offers realistic data generalization performance estimation in domain shifts typical of actual manufacturing. Findings indicate that a conventional Hybrid AE-LSTM model can make correct mean predictions but it

results in non-physical RUL oscillations. The monotonicity constrained model removes these inconsistencies and gives physically sensible degradation patterns.

The structure decreases RMSE to 0.1819 to 0.1700 on the invisible test bearing which indicates physics-inspired constraints increase interpretability and predictive accuracy. The results obtained confirm the hypothesis that combining unsupervised feature learning, supervised temporal modeling, and domain knowledge can generate realistic predictive maintenance solutions with accurate RUL prediction in industrial settings with under-labeled data and limited computational resources.

Future Work

Advanced Degradation Modeling: The linear RUL labeling approach is simplified. Future work should explore adaptive/piecewise degradation models capturing realistic failure modes including accelerated degradation cycles and multi-stage wear patterns common in rotating machinery.

Uncertainty Quantification: Implementing probabilistic frameworks (Bayesian LSTMs, Monte Carlo dropout, ensemble models) would enable confidence-aware RUL estimation with prediction intervals. This is critical for risk-sensitive maintenance decisions where practitioners balance maintenance costs against failure risks based on prediction uncertainty.

Multi-Sensor Fusion and Transfer Learning: The framework should incorporate multi-modal sensor data (vibration, temperature, acoustic emission) through sensor fusion. Transfer learning strategies could enhance generalization across bearing types, operating environments, and platforms while reducing data requirements for new equipment deployment.

Online Learning and Real-Time Deployment: Practical implementation requires addressing real-time inference on edge devices, online model updates with streaming data, and adaptive learning that continuously improves predictions as new operational data arrives—essential for dynamic industrial continuous monitoring.

These directions would transform the framework into a comprehensive, practical predictive maintenance solution balancing accuracy, interpretability, computational efficiency, and real-world manufacturing deployment.

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