Enhancing Realistic Remaining Useful Life Prediction through Multi-fidelity Physics-Informed Approaches

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ABSTRACT

Accurately predicting the remaining useful life (RUL) of components is challenging due to trend uncertainty in data-driven methods and limited data availability. To address these issues, this study proposes a multi-fidelity (MF) approach that combines low-fidelity (LF) and high-fidelity (HF) data to estimate RUL. By predicting discrepancies between the two data sets using a neural network, the proposed method leverages a physical model and artificial neural networks to enhance RUL estimation. The study focuses on performance degradation prediction using an exponential function as the LF model and monitoring data as the HF model. The exponential function's monotonically increasing trend contributes to realistic RUL predictions. The proposed approach is evaluated on rotating components, such as bearings and unbalanced cooling fans, to assess its generalization performance. Comparisons with existing techniques like long short-term memory (LSTM), autoregressive integrated moving average (ARIMA), and neural network (NN) highlight the unrealistic RUL prediction issues they face. The experimental results demonstrate that the proposed method produces accurate and realistic RUL predictions. It offers practical benefits in terms of cost reduction and improved operational efficiency. Overall, the MF approach addresses the limitations of traditional methods by integrating physical models, neural networks, and available monitoring data. This approach enables more reliable RUL predictions, facilitating effective maintenance decision-making for optimal asset management.

1. INTRODUCTION

The prediction of RUL has garnered attention for its potential in preventing serious component or system failures, workplace safety, and reducing costs. As components and machines operate continuously, they undergo degradation, leading to eventual failure. RUL prediction plays a crucial role in addressing this issue. However, RUL predictions may not always yield realistic results.

Predicting RUL as part of prognostics is challenging because RUL predictions are required to be accurate, reflecting future conditions based on available degradation data up to the current time. Data-driven methods, such as NN, LSTM, or ARIMA, are the most common approaches used for predicting RUL. Unfortunately, these algorithms work effectively when monitoring data of the operating components are available for their entire lifespan (run-to-failure data) during training. In other words, if the training data only extends up to the current time, both machine learning and deep learning encounter difficulties in predicting future degradation accurately, leading to challenges in estimating RUL realistically.

A realistic RUL prediction involves estimating the point at which degradation performance crosses the failure threshold. Unrealistic RUL predictions arise due to a method's inability to obtain accurate estimation model parameters from limited training data. Prognostic methods require the prediction of degradation performance in the future to generate RUL predictions. A recent study highlights the uncertainty in predicting realistic degradation performance (Kim et al., 2022), indicating that current methods such as machine learning and deep learning are insufficient to guarantee realistic RUL predictions. Machine learning performs optimally when trained with adequate data throughout the predictive model's interval. However, accurate RUL prediction is difficult due to insufficient data in the early stages of degradation.

Nonetheless, MF approaches combining machine learning with physical models have been studied in digital twinning and uncertainty quantification to address this problem (Motamed, 2020; Cutajar and Pullin, 2019). Physics-informed deep NN with a MF approach shows good regression performance (Meng et al. 2019). NNs were used to predict discrepancy using a physics-constrained approach for MF implementation (Liu et al. 2019). Deep NNs were utilized to predict discrepancies using a MF approach (Raissi et al., 2016). MF neural networks were used for efficient structural health monitoring, blending HF and LF data to enhance accuracy (Torzoni et al. 2023). The ability of the MF approach to handle the predictions of a more accurate model by providing a physical model has made several studies successful in implementing it. These approaches facilitate accurate performance prediction with limited data by combining a LF model representing degradation trends and a HF model for enhancing nonlinear predictive performance. Nevertheless, the study of MF focuses on high and LF models within a specific time range and does not involve predicting future performances without training data.

Hence, this study introduces a MF approach that leverages physical models to ensure a monotonically increasing degradation trend and employs machine learning to predict discrepancies, leading to realistic RUL predictions. This approach is applicable in cases where run-to-failure HF data is unavailable, while maintaining adherence to physical principles. The proposed multi-fidelity model is validated using two bearing failure cases. A comparative study of RUL prediction is conducted between the proposed method and LSTM, NN, and ARIMA models.

2. METHODOLOGY

The vibration monitoring data collected up to the current time serves as the HF data, while an exponential model representing monotonically increasing degradation is proposed as the LF model. By calculating the discrepancy between the HF and LF data from the initial predicted time to failure until the current time, a MF model is trained to predict the degradation performance. The scaling factor is assumed to remain constant at a value of 1 during the discrepancy calculation. The general form of the MF model can be expressed as low fidelity model y_L and discrepancy δ.

$$y_H = \rho y_L + \delta \tag{1}$$

Figure 1 provides an illustration of the available data and the expected realistic predictions for the RUL. To account for prediction uncertainty, only 60% of the available HF data is randomly selected as training data.

Using the previously calculated discrepancies from the high fidelity data y_L, future discrepancies are predicted using a NN. The NN structure consists of two hidden layers with rectified linear activation function (RELU) and five neurons in each hidden layer. The output layer uses a hyperbolic tangent (TANH) activation function to accommodate both negative and positive output predictions. The discrepancy prediction model is then combined with the physical model to estimate the degradation performance and RUL. The MF model and RUL can be calculated using equations (2) and (3), respectively.

$$\hat{y}_M = y_L + \hat{\delta}_{(t_0 \sim t_{EoL})} \tag{2}$$

$$\mathrm{RUL}\ (i) = \hat{t}_{fail}(i) - t_i \tag{3}$$

$\hat{\delta}_{(t_0 \sim t_{EoL})}$ represents the discrepancy prediction from the staring time of degradation until the end of life (EOL). $\hat{t}_{fail}(i)$ is defined as the time at which the MF model intersects with the failure threshold, where *i* ranges from 1 to *N*, with *N* being the total number of cycles. The incorporation of physical(degradation) model information that consistently increases positively ensures the realistic performance of the proposed method at all times.

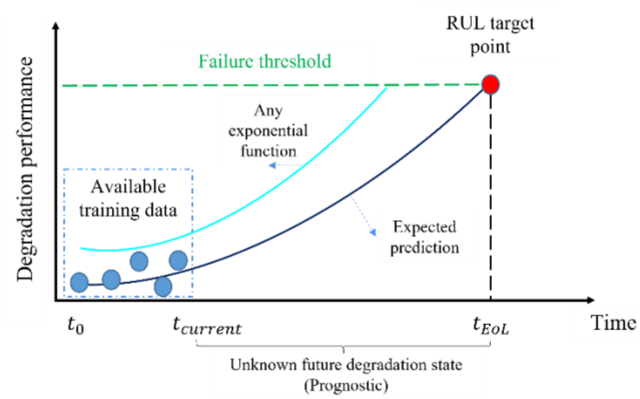


Figure 1. An illustration of the proposed method

3. CASE STUDY

Degradation models can be expressed in various ways, including constant failure rate, increasing degradation rate, and decreasing degradation rate. The data used in this study predominantly encompassed regions where the degradation rate was increasing. In cases where there were intervals with decreasing degradation rates, the accuracy of RUL predictions was improved using a discrepancy model.

3.1 Case 1: Imbalance cooling fan

The proposed method in this study will be evaluated using experimental data from an unbalanced cooling fan, referred to as Case 1. The cooling fan was subjected to an angular speed of 3,000 rpm and operated at a temperature of 70 ℃ within a controlled chamber. The obtained data from this experiment consists of acceleration measurements, which represent the vibration response. The vibration response is quantified using its root mean square (RMS) value calculated from training data, which serves as a degradation performance feature. Figure 3(a) illustrates the raw signal obtained from the measured data, while Figure 3(b) depicts the degradation performance data, which are modeled by an arbitrary exponential function. The failure threshold was determined the six-sigma RMS value. Figure 3 illustrates that the degradation does not follow a consistent increasing pattern and instead fluctuates, occasionally experiencing significant spikes. This variability poses a challenge for accurately predicting the remaining useful life (RUL) solely based on HF data.

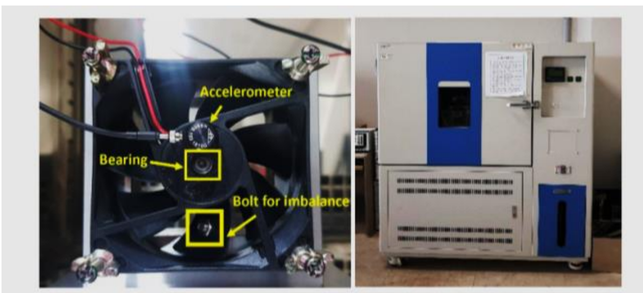
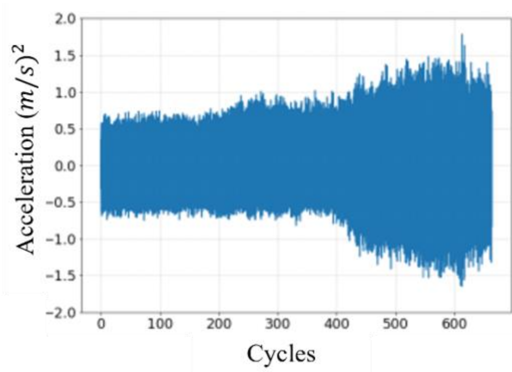
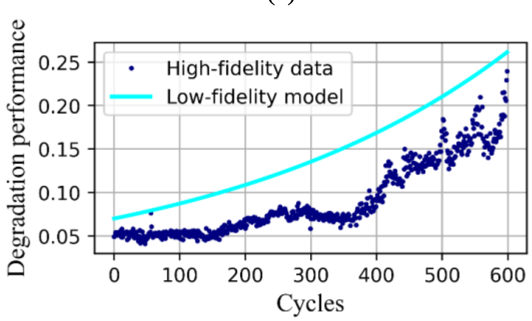


Figure 2. Experimental setup in Case 1



(a)

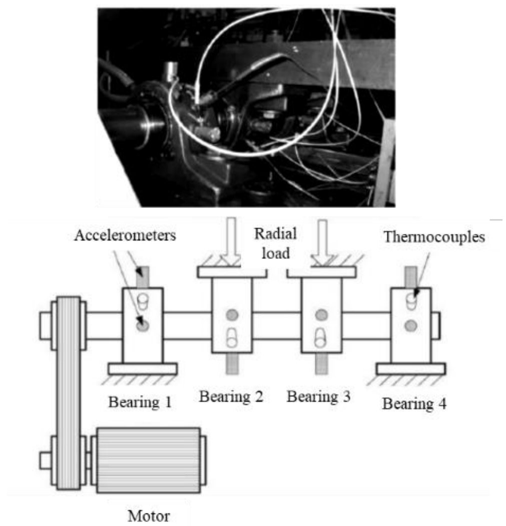


(b)

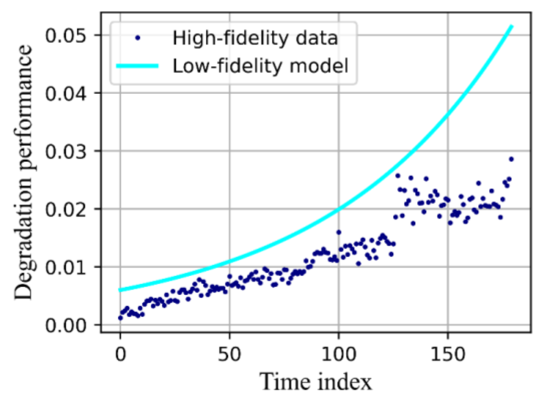
Figure. 3 Experiment data: (a) Acceleration response (b) Degradation performance

3.2 Case 2: Outer race bearing defect

Case 2 serves as a validation for the proposed method, aiming to enhance the generalization of the predictive model. It involves a failure in the outer race bearing due to a defect, as illustrated in Figure 4. The experimental data used in this study were obtained from tests conducted by the University of Cincinnati's Center for Intelligent Maintenance Systems (IMS) (Lee et al. 2007). As shown in Figure 4, the experiments were conducted on multiple bearings positioned on a mechanical system's shaft. The setup included a shaft rotating at a constant velocity of 2,000 rpm, supporting a load of 6,000 lb, utilizing a Rexnord ZA-2155 bearing type, and equipped with an accelerometer.



(a)



(b)

Figure. 4 Case 2: (a) Experimental setup and (b) degradation performance

The data collected in this experiment consists of the acceleration response, which is used to extract the degradation performance. The raw data undergo a transformation process to generate a spectrogram, which captures the highest amplitudes within specific time windows. Statistical features are then extracted from the spectrogram data and combined using principal component analysis (PCA). The resulting principal components are further smoothed using the Savitzky-Golay method. The RMS values of the health index (HI) start to change when the health condition undergoes a transition, allowing for the identification of the corresponding crossing time point. This point is referred to as the first predicted time to failure (FPTF), and the failure threshold for the HI data is determined using the six-sigma value. The specific details of the feature extraction process are not the main focus of this study and will not be discussed.

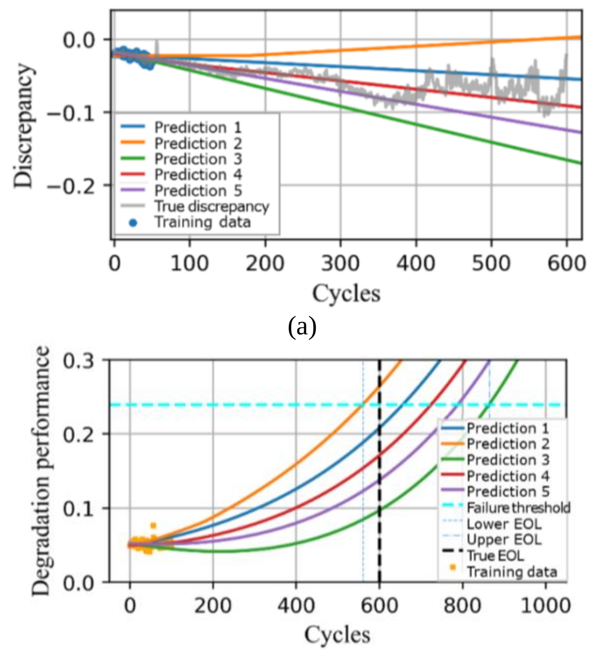
4. RESULT

4.1 RUL Prediction for Case 1

Five sets of discrepancy predictions are generated using randomly selected training data, and these results are depicted in Figure 5(a). It is observed that these predictions closely align with the true discrepancy within the first 50 data points, representing the available data up to the current time. Each of the five prediction results follows a linear trend, accompanied by some uncertainty in the discrepancy prediction. Despite this uncertainty, the discrepancy prediction results remain favorable as they exhibit proximity to the underlying true discrepancy. The linearity of the discrepancy prediction has implications for the prediction of monotonic degradation performance, considering that the LF models constructed from exponential functions also demonstrate a monotonically increasing behavior. This characteristic is beneficial in the prognostic process, as it reflects the expected trend of increasing degradation over time in the component.

Figure 5(b) shows the five predictions of degradation performance. These five predictions show realistic results because all performance degradation predictions cross the failure threshold. The difference between the time at which the degradation performance function intersects the failure threshold and the actual occurrence of failure represents the RUL. The calculated RUL values using the five predicted degradation models are 560, 657, 725, 789, and 864 cycles, respectively, and they show similar results compared to the actual RUL value. This demonstrates that even with limited available training data, the proposed MF model allows for realistic RUL estimation.

On the contrary, when there is limited data available up to the current system condition, other data-driven methods fail to predict RUL realistically, resulting in infinite RUL predictions. In Figure 6, degradation performance prediction results are presented using limited monitoring data from the initiation of degradation up to the current time through an additional random sampling approach. Data-driven models like LSTM and NN, which heavily rely on training data, produce degradation performance predictions that lack cross-failure thresholds, leading to unrealistic RUL predictions. Although ARIMA can accurately capture the time series trend, it tends to underestimate the degradation trend. In contrast, the proposed method demonstrates realistic RUL prediction results that align with the degradation trend based on the available training data. Figure 7 presents box plots depicting the RUL prediction results for five random training datasets, illustrating the impact of the number of training data on the predictions. As the number of training data increases, the RUL While the predicted RUL tends to overestimate the true RUL, it remains consistently close to the true RUL across different numbers of training data.



(a)

(b)

Figure 5. Prediction results for Case 1 (a) Discrepancy prediction and (b) Degradation performance and RUL prediction results

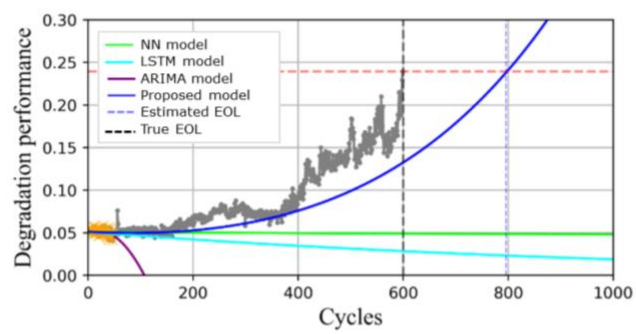


Figure 6. Degradation prediction results using various models

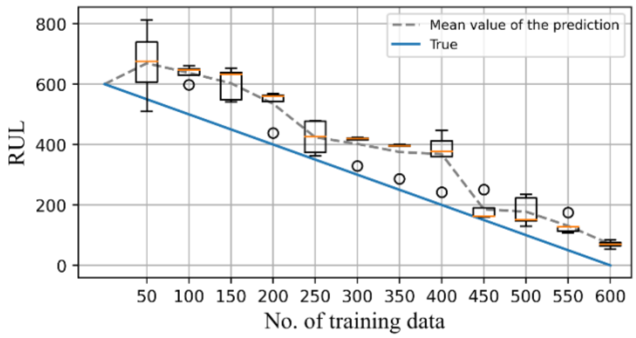


Figure 7. RUL predictions results for Case 1

4.2 RUL Prediction for Case 2

In Case 2, only 20 randomly sampled data points were used for training, with 60% of these data points repeated five times. The smaller amount of training data in Case 2 compared to Case 1 is due to the lower availability of run-to-failure data in Case 2. The discrepancy prediction results in a linear trend because the NN model attempts to fit the training data, which also exhibits a linear trend. With five repetitions of training, the discrepancy prediction shows low uncertainty, indicating that the NN model is robust.

The linear predictions of discrepancies have a significant impact on generating a monotonic and realistic degradation performance trend, as depicted in Figure. 8. The RUL prediction in Case 2 demonstrates low uncertainty and aligns well with the true RUL, occurring at a time index of 123 compared to the true RUL of 180. Moreover, these five predictions collectively provide a realistic model.

Compared to other methods such as ARIMA, NN, and LSTM, the proposed method outperforms in generating realistic predictions. Unlike ARIMA, NN, and LSTM, which can only provide accurate predictions up to the current time due to limited training data, the proposed method can predict performance degradation in future conditions. In Figure 9, the RUL prediction results obtained using the proposed method are displayed. Similar to the RUL results observed in Case 1, the predicted RUL results exhibit close proximity to the true RUL, regardless of the number of available data. As a result, the proposed method offers more reliable and realistic predictions beyond the current time, distinguishing it from the limitations of other methods.

This study employed an exponential function as the LF model. However, the predictive RUL results can vary based on the characteristics of the LF model (Kennedy and O'Hagan, 2001). Therefore, in future research, the optimization of coefficients used in the exponential function will be carried out to derive an LF model that effectively captures the degradation pattern while exhibiting a monotonically increasing trend.

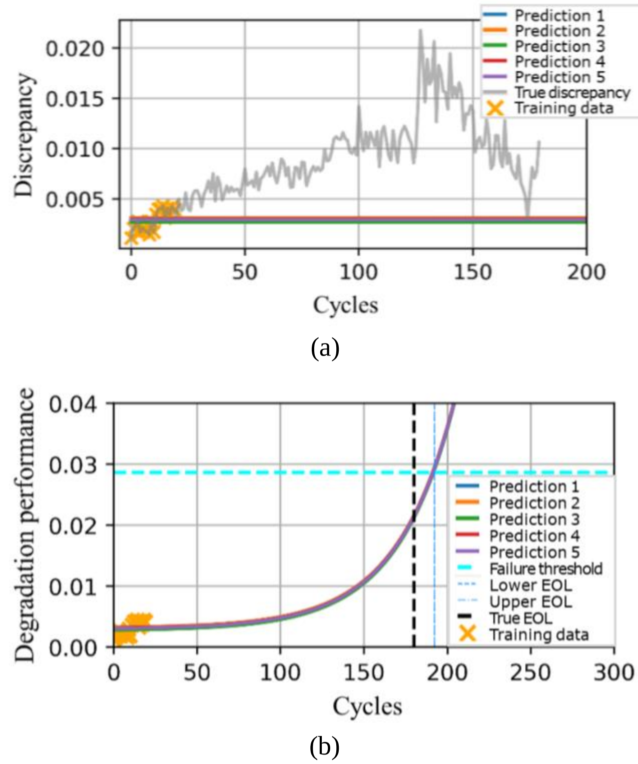


Figure. 8 Degradation performance prediction results for Case 2: (a) Discrepancy prediction (b) Degradation performance and RUL prediction

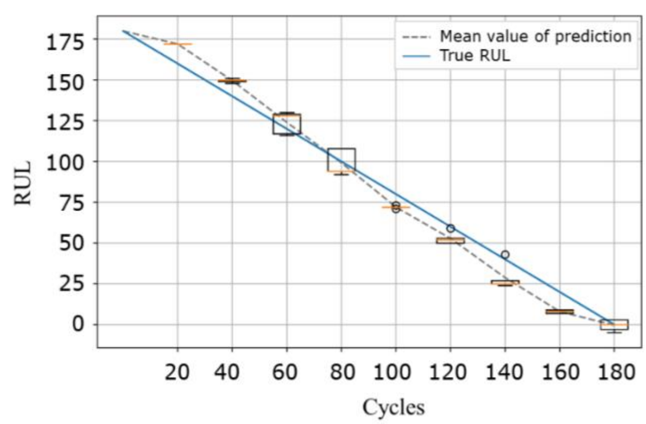


Figure 9. RUL prediction results for Case 2

5. CONCLUSION

To ensure robust and accurate predictions of RUL during the early stages of degradation, the proposed method combines a LF model with a monotonically increasing behavior and HF data. This approach surpasses other data-driven models or time series prediction models that solely rely on early degradation data. Precise RUL predictions in the early stages are critical for reducing maintenance costs and improving operational safety and efficiency. It is important to note that the results may vary depending on the scaling factor ρ. Hence, the study aims to optimize the parameters by considering the distinctive characteristics of the data and types of the LF models, thereby further enhancing the robustness and precision of RUL predictions.

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