

Physics-Informed Machine Learning For Motor Bearing Health Prognosis

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Physics-Informed Machine Learning for Motor Bearing Health Prognosis

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I. INTRODUCTION AND BACKGROUND

Rolling bearings are critical components in rotating machinery such as electric motors. According to reports by the IEEE Industry Application Society and the Japan Electrical Manufacturers' Association, bearing faults account for 30% to 40% of all motor failures [1], leading to reduced efficiency, serious safety risks, and significant downtime. Therefore, monitoring bearing health is essential to enable proactive maintenance.

To prevent such events, extensive research has analyzed vibration signals caused by degraded bearings [2], [3]. Classical methods model the interaction between defects and rolling elements as periodic impacts, which in turn excite structural resonance at characteristic defect frequency [4], [5]. These methods were initially developed to address localized defects, such as cracks and spalls, and were later extended to distributed defects such as surface waviness.

Besides these signal-processing developments, first-principles dynamic models have also been developed to elucidate the physics governing bearing vibrations under geometric imperfections [6]. In these models, the

Hamrock–Dowson model is employed to quantify the film thickness at bearing-race contacts with elastohydrodynamic lubrication (EHL) [7]. However, most physics-based models typically assume constant lubricant film thickness and surface roughness, ignoring the fact that these states evolve over time as the bearing degrades. In contrast, studies in the tribology community have shown that lubrication regimes fundamentally govern wear mechanisms, and that the lubricant parameter λ , defined as the ratio of lubricant film thickness to contact surface roughness, serves as a meaningful health indicator that is closely linked to bearing vibration behavior [8].

In recent years, data-driven [9], [10] and physics-informed machine-learning (PIML) approaches [11], [12] have advanced significantly for bearing fault detection. However, existing studies do not explicitly link vibration measurements with tribological knowledge or model the temporal dynamics of tribological states. Thus, reliable bearing health prognosis and remaining useful life (RUL) prediction remain challenging.

The main contributions of this work are summarized as follows.

- We develop a PIML framework that couples (i) neural-network-based evolution laws for lubricant film thickness and surface roughness, (ii) a vibration model that links the time-varying lubricant parameter $\lambda(t)$ to stochastic metal-to-metal impacts, and (iii) statistical vibration indicators commonly used in condition monitoring.
- We validate the framework experimentally on a motor-bearing system under two lubrication conditions. The trained model accurately reproduces multiple statistical vibration indicators on validation data.
- We demonstrate that the trained model can simulate future trajectories of $\lambda(t)$, enabling RUL estimation based on physically meaningful thresholds and yielding a more interpretable health indicator than raw vibration metrics.

II. PRELIMINARIES OF PHYSICAL MODEL

A. Vibration Model

Consider a motor-bearing system in which an accelerometer is mounted on the motor housing to measure the bearing vibration for health monitoring. During operation, the rotating rotor induces two types of vibration.

The first type of vibration arises from intermittent metal-to-metal contact that evolves over time, commonly referred to as impact vibration. This component can be formulated in terms of acceleration as [5]

$$a_{\text{impact}}(t) = \sum_{i=1}^n A_i e^{-\frac{t-t_i}{\tau}} u(t-t_i) \sin(\omega_r(t-t_i)), \quad (1)$$

where A_i denotes the amplitude of the i^{th} impact; τ is the decay time constant; $u(t)$ is the Heaviside step function defined as $u(t) = 1$ for $t \geq 0$ and $u(t) = 0$ for $t < 0$; n is the total number of impacts; t_i represents the occurrence time of the i^{th} impact; and ω_r is the dominant resonance (carrier) frequency of the motor-bearing system. For simplicity, only a single dominant resonance frequency is assumed.

The second type of vibration arises from geometrical imperfections, such as rotor mass imbalance or bearing surface waviness, and typically consists of harmonic components of the shaft rotation frequency. The harmonic vibration can be expressed as

$$a_{\text{harmonics}}(t) = \sum_{j=1}^m B_j \sin(\omega_j t + \phi_j) \sin(\omega_r t), \quad (2)$$

where B_j , ω_j , and ϕ_j are the amplitude, angular frequency, and phase of the j^{th} harmonic component, respectively, and m is the total number of harmonics. Because this type of vibration originates from manufacturing imperfections and assembly tolerances, it is present even in healthy bearings.

Combining these vibration components, the overall vibration model can be expressed as

$$a(t) = a_{\text{impact}}(t) + a_{\text{harmonics}}(t) + n(t), \quad (3)$$

where $n(t)$ represents additive measurement noise.

B. Lubrication Regime and Wear Evolution

For a bearing without localized defects, the metal-to-metal contacts described in (1) are modeled as a stochastic process arising from surface roughness, lubrication starvation, or a combination of both. The impact amplitudes A_i are therefore treated as random variables drawn from a zero-mean Gaussian distribution whose standard deviation depends on the lubrication parameter $\lambda(t)$. Specifically,

$$A_i \sim \mathcal{N}(0, \sigma(\lambda(t))), \quad (4)$$

where $\sigma(\lambda(t))$ characterizes the intensity of metal-to-metal interactions and reflects the evolving lubrication condition.

Extensive studies [13]–[15] have shown that the lubrication parameter $\lambda(t)$ in (4) serves as a key indicator of the lubrication regime. It is defined as

$$\lambda(t) = \frac{h_{\min}(t)}{\sigma_c(t)} = \frac{h_{\min}(t)}{\sqrt{\sigma_{\text{race}}^2(t) + \sigma_{\text{ball}}^2(t)}}, \quad (5)$$

where $h_{\min}(t)$ denotes the minimum lubricant film thickness between the raceways and balls, and $\sigma_c(t)$ is the combined surface roughness accounting for both the race surface roughness $\sigma_{\text{race}}(t)$ and the rolling-ball surface roughness $\sigma_{\text{ball}}(t)$. Here t represents time. The surface roughness is defined as the root-mean-square (RMS) deviation of the actual surface height from its mean value. Based on the value of $\lambda(t)$, the lubrication condition can be classified into three distinct regimes: fully flooded ($\lambda \geq 3$), mixed ($1 < \lambda < 3$), starved ($\lambda \leq 1$). When $\lambda(t) \geq 3$, the lubricant forms a complete elastohydrodynamic lubrication (EHL) film. Under this condition, the minimum lubricant film thickness $h_{\min}(t)$ is the EHL thickness h_{EHL} . When $1 < \lambda(t) < 3$, a partial EHL film is formed and asperity contact occurs intermittently. The average vibration magnitude increases in the mixed regime. When $\lambda(t) \leq 1$, hydrodynamic effects are insufficient to separate the contact surfaces, and the applied load is primarily supported by solid-to-solid contacts. This leads to accelerated bearing wear, ultimately resulting in rapid fatigue failure.

III. PHYSICS-INFORMED MACHINE LEARNING MODEL

A. Neural Networks for Lubrication and Roughness Evolution

Despite the empirical understanding of the relationship between $\lambda(t)$ and bearing health, the minimum lubricant film thickness $h_{\min}(t)$ and the combined surface roughness $\sigma_c(t)$ are not directly measurable in practice, and their temporal evolution during operation is generally unknown. Consequently, our objective is to estimate both the instantaneous value and the evolution of $\lambda(t)$ from vibration data. To this end, we first model the unknown dynamics of $h(t)$ and $\sigma_c(t)$. Assume that the evolution of these variables follows

$$\begin{cases} \frac{dh(t)}{dt} = f_h(h(t), \sigma_c(t)) \\ \frac{d\sigma_c(t)}{dt} = f_\sigma(h(t), \sigma_c(t)), \end{cases} \quad (6)$$

where $f_h(\cdot, \cdot)$ and $f_\sigma(\cdot, \cdot)$ denote unknown nonlinear dynamics. By representing the unknown dynamics using neural networks (NNs) under a discrete-time formulation, we obtain

$$\begin{cases} h((k+1)\Delta t) = h(k\Delta t) + \text{NN}_h(h(k\Delta t), \sigma_c(k\Delta t); \theta_h) \\ \sigma_c((k+1)\Delta t) = \sigma_c(k\Delta t) + \text{NN}_\sigma(h(k\Delta t), \sigma_c(k\Delta t); \theta_\sigma), \end{cases} \quad (7)$$

where $k \geq 0$ denotes the discrete time-step index, Δt is the sampling interval, and $\text{NN}_h(\cdot, \cdot; \theta_h)$ and $\text{NN}_\sigma(\cdot, \cdot; \theta_\sigma)$ represent NNs parameterized by θ_h and θ_σ , respectively. We assume that surface roughness begins to increase only after the bearing enters the mixed lubrication regime, i.e., the roughness growth rate $d\sigma_c/dt$ can become positive only when the lubricant film thickness satisfies $h(t) < h_{\text{EHL}}$. We

softly embed this physical constraint into the modeling of the roughness evolution. Specifically, the roughness-evolution network is formulated as

$$\text{NN}_\sigma(\cdot, \cdot; \theta_\sigma) = G(h(t); h_{\text{EHL}}) \cdot o^{(L)}(\cdot, \cdot; \theta_\sigma), \quad (8)$$

where $o^{(L)}(\cdot, \cdot; \theta_\sigma)$ is the output of the last layer of the L -layer NN parameterized by θ_σ , and $G(\cdot; \cdot)$ is a gating function that enforces the lubrication-dependent activation of roughness growth. The gating function is defined as

$$G(h(t); h_{\text{EHL}}) = \frac{1}{1 + \exp(-g * (h_{\text{EHL}} - h(t)))}, \quad (9)$$

where g is a tunable gain parameter controlling the sharpness of the transition. This formulation ensures that roughness evolution is suppressed under full-film EHL conditions and is gradually activated as the lubrication state transitions into mixed or boundary regimes.

Note that the evolutions of $h(t)$ and $\sigma_c(t)$ occurs on a slow time scale. Accordingly, the time step Δt used to simulate the discrete dynamics in (7) is relatively large (i.e., $\Delta t = 3,600$ s). This time scale is fundamentally different from that used for vibration simulation in (1)-(3), where the vibration signal is generated over a much shorter duration (i.e., 60 s) with a sampling frequency of 10 kHz. In the discrete-time formulation, the lubricant parameter $\lambda(t)$ is computed as

$$\lambda(k\Delta t) = h(k\Delta t) / \sigma_c(k\Delta t). \quad (10)$$

During training, the NN parameters $\theta_{\text{nn}} = \{\theta_h, \theta_\sigma\}$, along with the system's initial states $\theta_{\text{ic}} = \{h(0), \sigma_c(0)\}$, are jointly optimized and identified from data.

B. Vibration model re-parameterized for machine learning

Assume that, under normal operation before bearing failure, the bearing operates either in a fully flooded or partially flooded lubrication regime. In this situation, we bound the value of λ from below by 1 as

$$\lambda_{\text{eff}}(k\Delta t) = \max(1, \lambda(k\Delta t)). \quad (11)$$

Motivated by the reciprocal relationship between vibration RMS and λ [16], the standard deviation of the Gaussian distribution governing impact amplitudes is modeled as

$$\sigma(\lambda(k\Delta t)) = \frac{\alpha_0}{\lambda_{\text{eff}}^{\alpha_1}(k\Delta t)}, \quad (12)$$

where $\theta_g = \{\alpha_0, \alpha_1\}$ are unknown parameters to be identified during training. The use of λ_{eff} ensures numerical stability by preventing unrealistically small values of λ . To retain differentiability of the computational graph and allow gradients to back-propagate through the stochastic sampling process, we reformulate (4) using the re-parameterization trick [17]:

$$A(t; \lambda(k\Delta t)) = \sigma(\lambda(k\Delta t)) \cdot \epsilon(t), \quad \epsilon(t) \sim \mathcal{N}(0, 1), \quad (13)$$

where ϵ is a Gaussian white-noise sequence generated once at the beginning of training and held fixed throughout both

training and testing. Similarly, the measurement noise term $n(t)$ in (3) is re-parameterized as

$$n(t) = \mu_n + \sigma_n \cdot \epsilon(t), \quad \epsilon(t) \sim \mathcal{N}(0, 1), \quad (14)$$

where $\theta_n = \{\mu_n, \sigma_n\}$ denotes the noise parameters to be estimated.

The Gaussian distribution parameters θ_g , the noise parameters θ_n , and the impact decay time constant τ in (1) together form the acceleration model parameter set $\theta_{\text{accel}} = \{\theta_g, \theta_n, \tau\}$, which is jointly identified during training.

By combining (13) with (1), the vibration signal corresponding to the k^{th} discrete lubrication state is simulated as

$$a_k = \{a(k\Delta t), a(k\Delta t + \Delta t'), \dots, a(k\Delta t + l\Delta t')\}, \quad (15)$$

where l is the number of vibration samples generated per lubrication step and $\Delta t'$ is the vibration sampling interval. Note that $\Delta t \gg l\Delta t'$, reflecting the separation between the slow lubrication dynamics and the fast vibration dynamics.

C. Loss Function

The proposed framework trains the model so that statistical indicators computed from simulated vibration match those from measured vibration.

Following [3], we use RMS and sparsity-based features, including spectral entropy (SE), the ℓ_2/ℓ_1 ratio (R_{21}), and the Hoyer index (Hy), as target health indicators. These metrics are defined as

$$\text{RMS} = \sqrt{\frac{1}{T} \int_0^T a_{\text{HP}}^2(t) dt}, \quad (16)$$

$$\text{SE} = - \sum_{i=1}^N p(f_i) \log p(f_i),$$

$$\text{with } p(f_i) = \frac{E(f_i)}{\sum_{j=1}^N E(f_j)}, \quad (17)$$

$$R_{21} = \|E(f)\|_2 / \|E(f)\|_1, \quad (18)$$

$$\text{Hy} = \left(\sqrt{N} - \|E(f)\|_1 / \|E(f)\|_2 \right) / (\sqrt{N} - 1), \quad (19)$$

where $a_{\text{HP}}(t) = (a * h_{\text{HP}})(t)$ denotes the high-pass-filtered vibration signal; $h_{\text{HP}}(t)$ is the impulse response of the high-pass filter; T is the observation window; $E(f)$ is the spectrum of the envelope signal $e(t)$ extracted from a band-pass-filtered vibration signal $a_{\text{BP}}(t) = (a * h_{\text{BP}})(t)$ using the Hilbert transform; and N denotes the number of frequency bins.

The data loss $\mathcal{L}_{\text{data}}$ is defined as a weighted sum of the errors in the selected statistical indicators

$$\begin{aligned} \mathcal{L}_{\text{data}} &= w_0 \mathcal{L}_{\text{RMS}} + w_1 \mathcal{L}_{\text{SE}} + w_2 \mathcal{L}_{R_{21}} + w_3 \mathcal{L}_{\text{Hy}} \\ &= \sum_{k=0}^m (w_0 |\text{RMS}_k - \text{RMS}_{\text{tr},k}| + w_1 |\text{SE}_k - \text{SE}_{\text{tr},k}| \\ &\quad + w_2 |R_{21,k} - R_{21,\text{tr},k}| + w_3 |\text{Hy}_k - \text{Hy}_{\text{tr},k}|), \end{aligned} \quad (20)$$

where X_k and $X_{\text{tr},k}$, for $X \in \{\text{RMS}, \text{SE}, R_{21}, \text{Hy}\}$, denote the simulated and measured values of the corresponding statistical indicators over the interval $t = [k\Delta t, k\Delta t + l\Delta t']$, respectively.

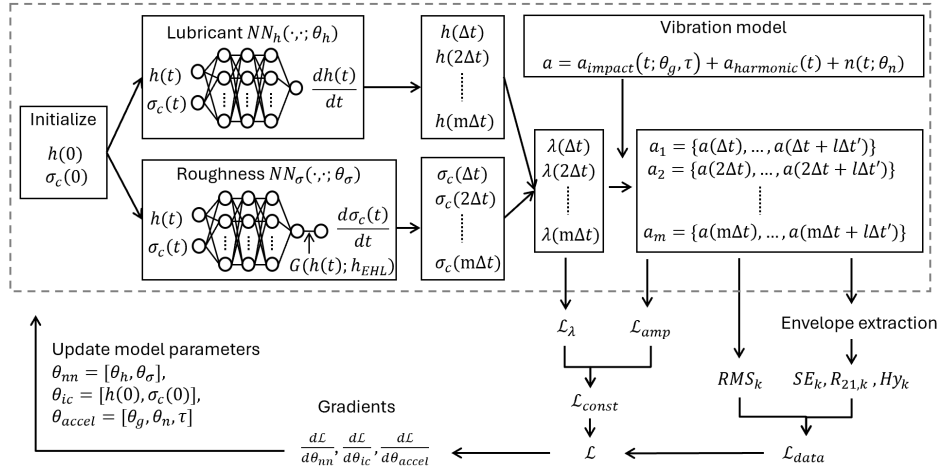


Fig. 1. Physics-informed machine learning pipeline.

The weight vector $w = [w_0, w_1, w_2, w_3]$ consists of hyper-parameters that balance the relative contributions of each indicator.

In addition to the aforementioned data-fidelity term, physics-based constraints are also imposed to guide the training process toward plausible solutions. First, assume that the bearing operates either in a fully flooded or mixed lubrication regime during normal operation, meaning $\lambda(t) \geq 1$. This constraint is enforced through the penalty

$$\mathcal{L}_\lambda = \sum_{k=0}^m \max(1 - \lambda(k\Delta t), 0). \quad (21)$$

Second, the amplitude of the simulated vibration is limited to the maximum amplitude observed in the measured vibration signal. This constraint is imposed via

$$\mathcal{L}_{\text{amp}} = \sum_{k=0}^m \max(0, (\max(|a_k|) - a_{tr, \max})) , \quad (22)$$

where $a_{tr, \max} = \max\{|a_{tr, 1}|, |a_{tr, 2}|, \dots, |a_{tr, m}|\}$. The loss function becomes

$$\mathcal{L} = \mathcal{L}_{\text{data}} + \mathcal{L}_\lambda + \mathcal{L}_{\text{amp}} . \quad (23)$$

The training objective is to identify model parameters $\theta = \{\theta_{nn}, \theta_{ic}, \theta_{\text{accel}}\}$ such that the total loss $\mathcal{L}$ is minimized, thereby encouraging physically plausible lubricant-film-thickness and surface-roughness dynamics.

D. Overall Pipeline

The overall physics-informed machine learning pipeline, which integrates the process described in Sections III-A-III-C, is illustrated in Fig. 1. For each dataset containing the true statistical health indicators of the measured vibration signal at discrete time points, the pipeline proceeds as follows.

Starting from initial states θ_{ic} , the neural networks NN_h and NN_σ are used to generate time sequences of lubricant film thickness $h(t)$ and surface roughness $\sigma_c(t)$ via (7). These

quantities are then combined to compute the corresponding lubrication parameter $\lambda(t)$ using (10).

At each discrete time step, the value of $\lambda(t)$ is used to determine the amplitude of stochastic metal-to-metal impact process $A(t)$ over a duration of $l\Delta t'$ through the re-parameterized formulation in (13). The impact vibration component $a_{\text{impact}}(t)$ is then computed using (1), and combined with the harmonic and noise components to generate a simulated vibration sequence $a(t)$ over the corresponding interval via (3).

From each simulated vibration segment $a(t)$, the four statistical indicators, RMS, spectral entropy (SE), R_{21} , and the Hoyer index (Hy) are computed. These simulated indicators are then compared with their measured counterparts to evaluate the data loss $\mathcal{L}_{\text{data}}$ using (20). Additional physics-based penalty terms are computed from the simulated states to form the constraint losses, and the total loss $\mathcal{L}$ is obtained as defined in (21)-(23). Finally, the parameter set θ is updated by gradient-based optimization in the direction that minimizes the total loss.

IV. EXPERIMENTS AND RESULTS

A. Experimental Setup for Data Collection

To obtain vibration data from bearings with different lubricant conditions, two deep-groove ball bearings of the same type (NSK 6306C3E) were prepared. The original lubricant in both bearings was removed using an alcohol solution, after which lubricant volumes of $4 \mu\text{L}$ and $2 \mu\text{L}$ were applied to the respective bearings. For each experiment, one bearing was mounted on the shaft of a three-phase induction motor (Hitachi 3.7kW TFO-LK 4P), and an accelerometer was attached to the top of the motor housing. The bearings were left unsealed to accelerate lubricant depletion during operation. The motor was operated at 1,800 RPM without external load for a total duration of 27 h and 120 h for the bearings lubricated with $4 \mu\text{L}$ and $2 \mu\text{L}$ of lubricant, respectively. These two datasets are denoted as *Data1* and *Data2*. Vibration signals were recorded periodically, approximately every 1-2 h over 60 s intervals with a sampling frequency of 10 kHz.

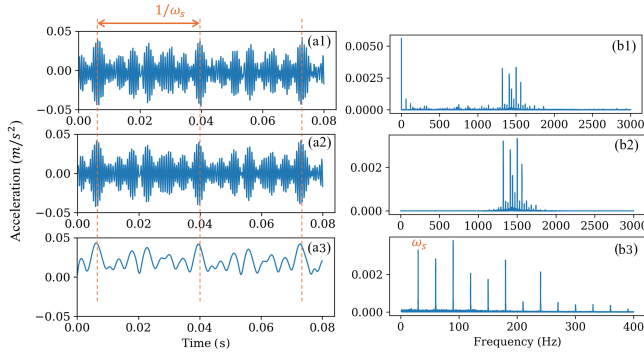


Fig. 2. Signal-processing results for extracting harmonic components from healthy vibration: (a1) raw signal $a(t)$, (a2) band-pass-filtered signal $a_{BP}(t)$, (a3) extracted envelope signal $e(t)$ and (b1)-(b3) the corresponding Fourier spectra of (a1)-(a3), respectively. Parameter ω_s denotes the shaft rotational frequency.

The entire *Data1* and the first 70 h of *Data2* were used as the training dataset, while the remaining portion of *Data2* was reserved for validation. The first vibration measurement for *Data1* was assumed to represent a healthy bearing condition and was used to calibrate the harmonic vibration component $a_{\text{harmonics}}(t)$ according to the procedure described in II-A.

B. Training and Validation

Initial conditions $\{h_i(0), \sigma_{c,i}(0)\}$ for training datasets $i \in \{1, 2\}$ are jointly optimized during training and are used to simulate the corresponding trajectories of $h(t)$ and $\sigma_c(t)$ via (7). According to the experimental setup, constraints on initial states $h_1(0) = 2h_2(0)$ and $\sigma_{c,1}(0) = \sigma_{c,2}(0)$ are imposed during training.

Both the film-thickness model (NN_h) and the surface-roughness model (NN_σ) are implemented as small multilayer perceptrons, each consisting of two hidden layers with 16 neurons per layer and hyperbolic tangent ($\tanh$) activation functions. The time step $\Delta t = 3600$ s is used for modeling the slow evolution of lubrication states, while $\Delta t' = 2$ s is used for fast impact simulation. Training is performed end-to-end over full trajectories from both datasets (*Data1* and *Data2*). The model is optimized for 30000 epochs using the Adam optimizer [18] with a learning rate of $\eta = 10^{-3}$. The loss weights $w = [0.85, 0.05, 0.05, 0.05]$ are used to combine the statistical-indicator losses into the data loss $\mathcal{L}_{\text{data}}$ (20). It takes approximately 4 hours to finish the training process on an NVIDIA A40 GPU. In validation, we use the trained model to predict the statistical indicators of the bearing vibration signal, given the initial states $\{h(0), \sigma_c(0)\}$ and the time window to be simulated. As illustrated in Fig. 3, the trained model achieves agreement between the simulated and measured statistical indicators using the trained model.

C. Estimation of Health Condition

Internally, the pipeline estimates the temporal evolution of the lubricant film thickness $h(t)$ and surface roughness $\sigma_c(t)$, from which the lubrication parameter $\lambda(t)$ is obtained, as shown in Fig. 4. As expected from the constraint embedded in

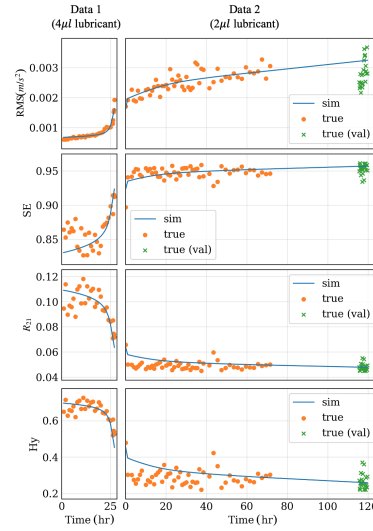


Fig. 3. Training results comparing simulated and measured statistical indicators (from top to bottom: RMS, SE, R_{21} , and Hy.) The blue curves denote simulated values, while the orange and green markers correspond to training and validation data, respectively.

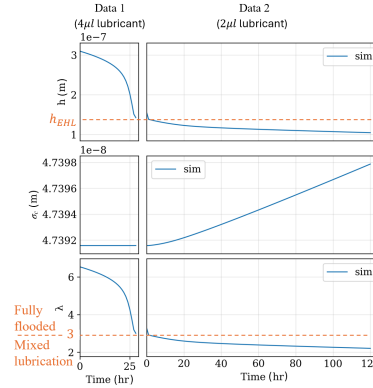


Fig. 4. Simulated lubricant film thickness $h(t)$ (top), surface roughness $\sigma_c(t)$ (middle), and lubrication parameter $\lambda(t)$ (bottom) after training.

the roughness neural network (8)-(9), surface roughness begins to increase once the lubricant film thickness falls below h_{EHL} . Notably, the transition coincides with the point at which $\lambda(t)$ drops below 3 and the bearing enters the mixed lubrication regime. This physically consistent behavior, which was not explicitly imposed during training, indicates the model's ability to uncover underlying physical mechanisms directly from data. The relatively rapid temporal variation of $\lambda(t)$ can be attributed to operation with unsealed bearings and without external load; the latter promotes increased skidding behavior, which can damage the lubrication film [19]. These results demonstrate that the proposed pipeline can successfully infer otherwise unmeasurable bearing health states, as represented by $\lambda(t)$.

D. RUL Prediction

The trained model can be used to simulate the future evolution of the lubrication parameter $\lambda(t)$, thereby enabling

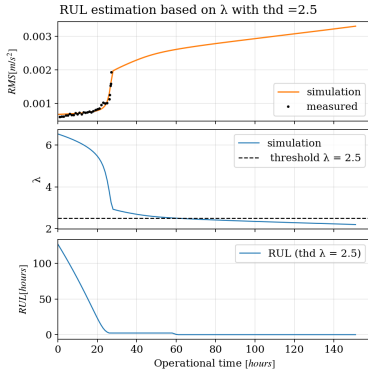


Fig. 5. Extended simulation results for *Data1* using the model trained on *Data1* and *Data2*. The bottom plot shows the predicted RUL based on the current degradation rate and a prescribed λ threshold.

estimation of the bearing's RUL. Given a maintenance threshold λ_{thd} defined in terms of $\lambda(t)$, the raw RUL estimate is

$$\widehat{\text{RUL}}(t) = \min \left\{ \text{RUL}(0) - t, \frac{|\lambda(t) - \lambda_{\text{thd}}|}{\max(-\Delta\lambda(t)/\Delta t, 0)} \right\}, \quad (24)$$

where $\text{RUL}(0)$ denotes the nominal useful life, i.e., the expected maximum operating time under normal conditions. The raw RUL estimate represents the projected time required for the target variable $\lambda(t)$ to reach the prescribed threshold λ_{thd} , based on the current degradation rate $-\Delta\lambda(t)/\Delta t$. When $\Delta\lambda(t) = 0$, the RUL is determined solely by the nominal useful life $\text{RUL}(0)$ and elapsed operating time t .

To enforce non-negativity and monotonicity of the RUL estimate, the following constraint is applied:

$$\text{RUL}(t) = \max \left\{ \min \left\{ \widehat{\text{RUL}}(t), \text{RUL}(t-1) \right\}, 0 \right\}. \quad (25)$$

To demonstrate this capability, an extended simulation is performed on *Data1* using the model trained on both *Data1* and *Data2*. A maintenance threshold of $\lambda_{\text{thd}} = 2.5$ is adopted, corresponding to the mixed lubrication regime. The resulting trajectories, together with the corresponding RUL estimates, are shown in Fig. 5. As predicted by the model, an increase in the measured vibration RMS is accompanied by a decrease in the estimated $\lambda(t)$, which is consistent with possible lubricant leakage and progressive surface roughening. Consequently, the predicted RUL decreases rapidly toward zero, indicating the need for maintenance intervention. Since this study focuses on bearings operating under lubricant-starved conditions that accelerate degradation, the operational time should be interpreted as a reference time scale for degradation progression rather than an absolute service lifetime.

V. CONCLUSION

This work presents a physics-informed machine learning framework for predicting the evolution of bearing health from vibration measurements. By coupling dual neural networks that model lubricant film thickness and surface roughness with a vibration model driven by the lubrication parameter λ , the proposed approach infers otherwise unmeasurable

health-related quantities using standard accelerometer data. Experimental results show that the proposed framework can accurately reproduce key statistical indicators of the vibration signal on held-out data and identify transitions toward mixed and starved lubrication regimes. Furthermore, it can simulate future trajectories of λ , thereby facilitating RUL estimation based on a physically meaningful threshold.

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