

Vibrations forecasting using physics informed machine learning: case-study of self-lubricated hydrodynamic journal bearings

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Highlights

1. Use of Bayesian inference on physics model to recover and track the evolution of the current machine parameters;
2. Forecasting of future vibrations states through all the life-time of a journal bearing on a pendulum-like test rig using neural operators;
3. Use a simplified physics model of the test rig to improve forecasts of its future vibration states using physics informed machine learning;
4. Use the data driven physics surrogate model of the test rig to improve forecasting of the physics informed machine learning.

Vibrations forecasting using physics informed machine learning: case-study of self-lubricated hydrodynamic journal bearings

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Abstract: Physics-informed machine learning (PIML) offers a powerful means of combining physical knowledge with data-driven models, potentially improving prediction accuracy, robustness, and interpretability. However, its application to condition monitoring and predictive maintenance remains limited. This study investigates a hybrid PIML framework for forecasting future vibration states from current measurements, addressing three key challenges in industrial applications: limited training data, incomplete knowledge of the underlying physics, and the absence of failure examples. The proposed framework combines approximate physical and physics-based surrogate models with Bayesian data-driven parameter correction during operation. A neural operator then forecasts vibration states in the model-parameter space, efficiently integrating physical knowledge and observed data. The approach is evaluated using vibration data from accelerated lifetime tests of self-lubricated hydrodynamic journal bearings. Distinct training and test datasets with no overlapping signals are used to ensure rigorous evaluation. The proposed framework is compared experimentally with conventional physics-informed methods and recent neural network architectures. It achieves forecasting errors below 25% for horizons exceeding 8 hours, while accurately capturing nonlinear vibration dynamics from limited data. It consistently outperforms the reference models and generalizes to operating conditions not represented in the training data. The generic architecture can be applied to systems with unavailable, incomplete, or difficult-to-reconstruct physical descriptions, demonstrating the potential of hybrid PIML for predictive maintenance and condition monitoring of complex engineering systems.

Keywords: Physics-informed machine learning, vibrational analysis, time-series forecasting, data-driven physics modelling, Gaussian processes.

1. Introduction

Although machine learning (ML) has been used to solve differential equations since the early 1990s [1,2], the concept of physics-informed machine learning (PIML) was formally introduced later by Karpatne et al. [3]. Raissi et al. [4] subsequently developed physics-informed neural networks (PINNs), which have become one of the most prominent PIML approaches and continue to receive substantial research attention [5–10].

PINNs have demonstrated efficiency across diverse fields, including fluid dynamics [8], chemistry [5], materials design [6], power grid analysis [7], and condition monitoring [8–10]. By incorporating governing physical equations into the learning process, PINNs combine physics-based modeling with improved convergence in complex settings. These capabilities make PINNs promising for vibration analysis, where system dynamics are complex. However, those architectures have inherent limitations, while other PIML remains relatively underexplored in vibration-based condition monitoring and predictive maintenance.

A key challenge for PINNs is the inherent uncertainty of physical vibration models. In practical applications, governing equations often require additional boundary conditions or correction terms to accurately capture system dynamics [13]. These quantities can be difficult to determine experimentally or may be entirely unknown, making the effectiveness of physics-informed approaches highly dependent on the accuracy and completeness of the underlying physical model.

Despite these limitations, several studies have demonstrated the potential of PIML and PINNs for vibration analysis. Yan et al. [11] applied a PINN-based framework to composite structures, combining physics-informed learning with extreme learning machines to reduce training data requirements. Zhuang et al. [12] introduced an energy-based PINN formulation for Kirchhoff plates, improving convergence and computational efficiency. Both studies, however, considered only free vibrations without external excitation.

Chen et al. [13] extended PINNs to forced vibrations of strings, beams, and plates by combining time marching with transfer learning, domain normalization, re-activation optimization, and sinusoidal activation functions. These modifications improved both predictive performance and computational efficiency.

More broadly, recent research has focused on developing increasingly accurate physics-based models for specific vibration problems to improve PINN performance. However, most approaches remain highly dependent on precise governing equations and boundary conditions, with limited attention to systems whose underlying physics is uncertain or only partially known [13–15]. Developing accurate physical models can be difficult, costly, or impractical, particularly for large-scale engineering systems [16] and degrading mechanical assemblies [15,16], where wear, evolving clearances, and changing component interactions produce complex and nonlinear vibration behaviour. In such cases, a complete physical description may be infeasible.

A natural solution is to combine physics-based models with data-driven estimation of unknown physical terms. This approach can recover unobserved variables and continuously adapt model parameters to changes in the monitored system, retaining the interpretability of physical models while leveraging the flexibility of ML. Several studies have introduced such adaptability into PIML. Söyleyici et al. [17] proposed an inverse-problem framework in which a PINN continuously identifies and tracks unknown physical parameters. Similarly, Kapoor et al. [20] applied PINN-based inverse modelling to highly nonlinear structural systems, accurately estimating displacements and rotations while inferring internal forces.

Zhang et al. [19] further extended this concept by developing a deep PINN for reconstructing unobserved states in distributed structures from sparsely deployed sensors. Using measured structural responses and known vibrational excitations, the framework estimates hidden system states by combining physical constraints with data-driven learning. From a system-identification perspective, this can be viewed as physics-guided black-box modelling, where ML reconstructs internal dynamics from observed inputs and outputs using only a coarse physical description as prior knowledge.

These studies highlight growing interest in hybrid physics-informed approaches capable of adapting to nonstationary dynamics. Building on this direction, the present work introduces a framework specifically designed to enhance adaptation to nonstationary cases.

First, the proposed approach is designed to operate with limited training data. Data acquisition in real-life is often costly and constrained by operational and safety requirements. Especially data collection is problematic for fault and failure data, which are difficult to reproduce, resulting in few representative examples. Such data scarcity can limit the generalization of conventional ML, including PINN-based approaches.

Second, the framework is designed to account for uncertainty and changes in the underlying physical model. In practice, parameters can deviate from nominal values due to tolerances, environmental effects, wear, and degradation, reducing the accuracy of model's assumptions. Updating conventional ML typically requires retraining, which can involve redefining training data and regularization terms and may introduce substantial computational costs and operational downtime. In contrast, the proposed framework uses adaptive parameter inference to track evolving system conditions without extensive retraining.

Third, the framework focuses on forecasting future vibration states rather than detecting already-existing faults or abnormal operating conditions. While conventional condition-monitoring methods primarily identify anomalies after they emerge, such conditions may already indicate significant degradation and leave limited time for corrective action. By forecasting vibration dynamics over extended horizons, the proposed approach aims to anticipate critical operating conditions and provide additional time for intervention.

To address these challenges, the proposed framework introduces several features that, to the best of the authors' knowledge, have not been previously explored in vibrational analysis. First, measured data are directly inferred through the underlying physics model without involving ML. This enables rapid online system updates without ML retraining. Specifically, Gaussian process-based inference involved for model correction during operation.

The framework also investigates physics-based surrogate models [23–25] as computationally efficient approximations of the underlying system dynamics. These models provide a practical alternative when accurate physics-based models are unavailable, incomplete, or computationally expensive to develop.

For long-horizon forecasting, neural operators (NOs) [18,35–37] are utilized in the parameter space of the physics-based model. Unlike conventional neural networks, which learn mappings between finite-dimensional input and output spaces, NOs learn mappings between functional spaces [35–37]. In the proposed framework, this enables the NO to learn the evolution of the underlying model parameters from their current to future states. Forecasting parameter evolution, rather than vibration signals directly, preserves the physical interpretability of the system representation while exploiting the strong generalization capabilities of NOs for nonlinear systems.

The remainder of the paper is organized as follows. Section 2 describes the problem, experimental setup, and data collection. Section 3 presents the physics-based and surrogate models, together with the ML

and inference methods. Section 4 discusses the results and future work. A lightweight version of the code is available in Git repository [29].

2. Experimental setup and data collection

The experimental data were collected using a customized Multiple Bearing Wear Tribometer (Mehrfach-Sinterlager-Verschleiß-Testgerät, MSVT), developed at AC2T research GmbH to investigate lubricated journal bearings (PJBs) [25]. The experiments used porous journal bearings pre-impregnated with lubricant to ensure continuous lubrication.

PJBs typically operate under hydrodynamic lubrication, where a lubricant film separates the bearing and shaft surfaces. During start-up and shutdown, reduced speed can cause a transition to mixed lubrication, increasing contact, friction, and wear. This behavior is relevant to start-stop applications such as windshield wipers and throttle valves [25,28], making PJBs suitable for studying wear evolution and vibration behavior.

The MSVT comprises five identical test benches, allowing simultaneous testing of up to five bearings under nominally identical conditions. This configuration improves statistical significance while reducing testing time. A detailed description is provided in Eder et al. [25,26,28]; only components relevant to the present vibration experiments are described here.

Each bench includes a sample holder (Figure 1a), a servo motor with frequency control for continuous unidirectional or oscillatory speed variation, and a heating system capable of reaching 180°C for elevated-temperature and accelerated lifetime testing [25]. Radial loading is applied through dead weights on a pendulum rod, with an oil-filled container providing passive damping [25]. The setup enables controlled variation of speed, temperature, and load during extended experiments.

The pendulum inclination, directly related to friction torque, is measured by three laser distance sensors arranged above the sample holder (Figure 1, b). Laser 1 measures the vertical displacement of the top plate; an increase in d_1 indicates a decrease in plate height and thus progressive bearing and shaft wear. Lasers

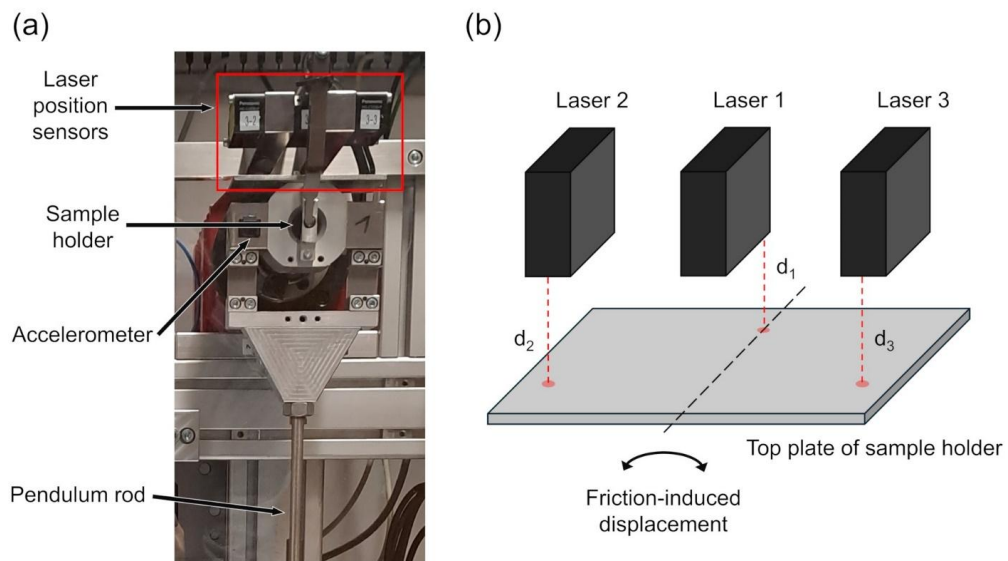


Figure 1: (a) Close-up image of the sample holder assembly at one test bench, (b) schematic sketch of geometric arrangement and measuring positions of the three laser position sensors. The dashed line indicates the center line of the top plate. The tilt of the top plate is defined by the displacement of the pendulum, as described in section 3.

2 and 3 measure pendulum inclination and vibration, providing information on the dynamic response of the tribological system.

The experiments followed the procedure described in [25,28] and used bronze- and iron-based porous journal bearings impregnated with lubricant before testing. A constant radial load of 250 N was applied, while the shaft speed followed a bidirectional sawtooth profile between -20 and $+20$ rpm with a 10 s period. This operating profile was selected to emulate start–stop conditions, which promote accelerated wear.

The sawtooth excitation was periodically interrupted by test runs after predefined intervals: initially at 1, 2, 3, 4, 5, 8, 11, 14, 17, 20, 28, 36, and 44 h, followed by regular 8 h intervals. Each run comprised three Stribeck ramps, with rotational speed increasing exponentially from 0 to 3000 rpm over 180 s. Laser distances, motor torque, and rotational speed were recorded at 5 Hz during sawtooth operation and at 2 kHz during the ramps to capture rapid dynamic effects.

The Stribeck ramps primarily represent hydrodynamic lubrication, transitioning to mixed lubrication at low speeds. This transition is evident in the measured signals (Figure 2 a,b), making the ramps suitable for tracking lubrication state and system degradation. Changes in the Stribeck response, such as increasing vibration amplitudes, may indicate lubricant degradation or starvation and provide early warning of critical operating conditions.

For our ML framework, the time between consecutive test runs defines the forecasting horizon. Although the Stribeck excitation is identical across all runs, the resulting torque response changes as the system degrades. The measured torque and prescribed excitation are used as inputs to the physics-based vibration model, while the laser measurements provide the corresponding vibration response. Representative torque, vibration, and speed signals are shown in Figure 2.

Stribeck ramping is a classical excitation strategy for black-box system identification in automatic control [27]. Run-up and coast-down cycles over a wide speed range systematically excite the system across its operating envelope, enabling identification of dynamic changes associated with increasing vibration or incipient failure. These changes appear as increasing deviations from the reference response curves, as illustrated in Figure 2, b.

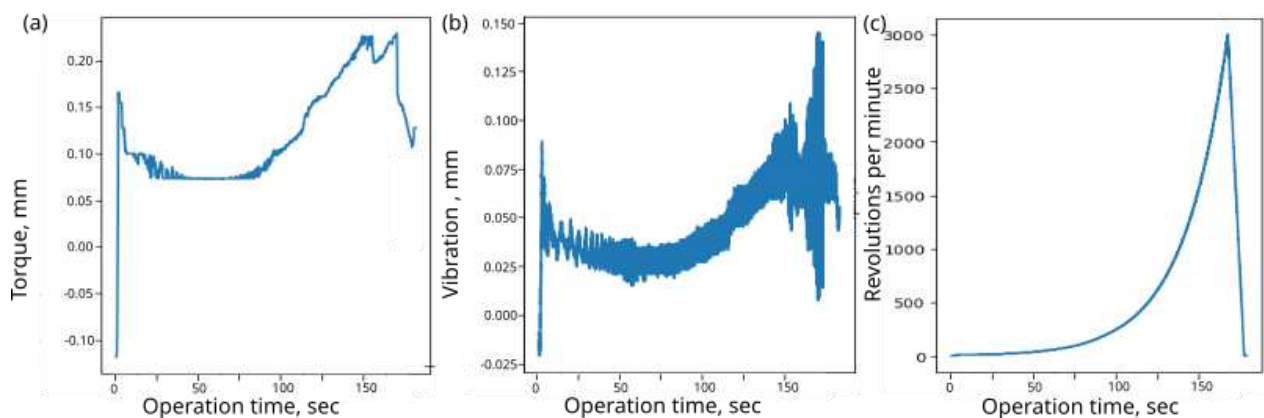


Figure 2: Example of measured signals for an individual test-run, performed after 8 hours of machine operation: (a) torque deviation of the system; (b) vibration response, measured by sensor "Laser 2" according to the setup shown in Figure 1, b; (c) corresponding Stribeck ramp. The Stribeck profile (c) is identical for all test runs, whereas the torque (a) and vibration (b) responses are unique for each test interval, reflecting the unique non-linear evolution of the system.

Models of the system

The proposed framework considers two modelling strategies. The first is a physics-based ODE model with physically meaningful parameters describing the system's vibrational behaviour. The second uses purely data-driven ODEs when a physics-based model is unavailable, incomplete, or prohibitively expensive. These physics-surrogate models reproduce the observed dynamics through empirical relationships with limited physical interpretability.

Building on recent surrogate modelling approaches for dynamic systems [22,23], this strategy offers a practical alternative for vibration-based condition monitoring under uncertain or evolving conditions, where its application remains largely unexplored.

3.1. Physics model

The physics model represents the MSVT as an idealized two-degree-of-freedom pendulum, as shown in Figure 3. The shaft is driven at constant speed, generating a viscous torque (T_τ) through the lubricant, which governs the pendulum motion. The first degree of freedom is the pendulum angle (θ), while the second, (β), accounts for rod deformation due to the concentrated mass at its lower end.

The viscous torque is balanced by the gravitational restoring torque $T_g = Mg \sin(\theta) L_{cm} \approx Mg L_{cm} \theta$, where M is the pendulum mass, g is the gravity acceleration and L_{cm} is the distance between the shaft axis and the pendulum mass center. The damping torque (T_b) from the oil is defined as $T_b = s L_{cm} \dot{\beta}$, where s is the

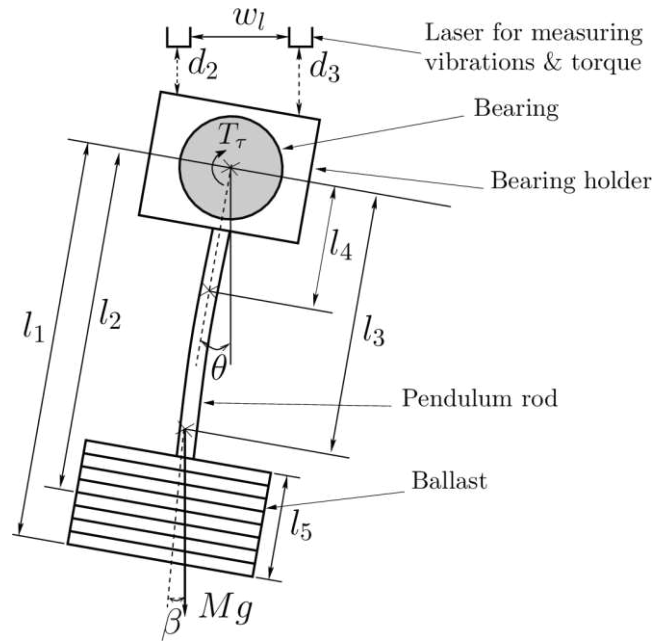


Figure 3: Schematic diagram of the MSVT showing the various dimensions and forces

effective damping coefficient, due to the oil bath. Rod deformation is represented as $T_p = F_p l_2$, where $F_p = -(3EI/l_2^3)w$, and $w = -l_2(\theta - \beta)$, with E as the elastic modulus of the rod, I the area moment of inertia of the rod and the length l_2 as shown in Figure 1.

The torque balance between the viscous torque and the bending torque is given by

$$J_p \ddot{\theta} = T_\tau - T_p, \quad (1)$$

where J_p is the mass moment of inertia of the pendulum rod. The balance between the bending torque and the torque due to the ballast is given by

$$J_b \ddot{\beta} = T_p - T_g - T_b, \quad (2)$$

where J_b is the mass moment of inertia of the ballast.

Equations (1) and (2) result in a set of coupled ordinary differential equations that governs the dynamics of the two angles, which can be written as

$$J_p \ddot{\theta} = T_\tau - \frac{3EI}{l_2}(\theta - \beta) \quad (3a)$$

$$J_b \ddot{\beta} = \frac{3EI}{l_2}(\theta - \beta) - sL_{cm}\dot{\beta} - MgL_{cm}\beta \quad (3b)$$

The initial conditions are given as

$$\theta|_{t=0} = 0 \text{ and } \dot{\theta}|_{t=0} = 0 \quad (4a)$$

$$\beta|_{t=0} = 0 \text{ and } \dot{\beta}|_{t=0} = 0 \quad (4b)$$

To identify the most important parameters influencing the dynamics, the physical variables are non-dimensional and rescaled as: $t = (1/\omega_0)t^*$, $\theta = (J_b/J_p)\theta^*$ and $\beta = \beta^*$, where the variables with an asterisk denote the non-dimensional or rescaled variables. Additionally, the torque at the bearing is scaled by a characteristic viscous torque as $T_\tau = (Ar_b^2\mu\omega_0/c)T_\tau^*$, where A is the area of the inner surface of the bushing, r_b is the radius of

Non-dimensional parameter	Expression	Physical interpretation
Π_e	$\frac{3EI}{J_b\omega_0^2 l_2}$	Effect of elasticity (or bending) relative to inertia
Π_v	$\frac{Ar_b^2\mu}{J_b\omega_0 c}$	Viscous effects in bearing relative to inertia
Π_g	$\frac{MgL_{cm}}{J_b\omega_0^2}$	Effect of gravitation relative to inertia
Π_d	$\frac{sL_{cm}}{J_b\omega_0}$	Effect of damping relative to inertia

Table 1 Definition of various non-dimensional numbers and their physical interpretations.

the shaft/bushing, μ is the dynamic viscosity of the lubricant, ω_0 is a characteristic angular speed of the shaft and c is the mean clearance between the shaft and the bushing.

Rewriting the torque balance of Eq. (3) in non-dimensional form and dividing the terms by $J_b \omega_0^2$ results in the following set of non-dimensional equations

$$\ddot{\theta}^* = \Pi_v T_\tau^* - \Pi_e (J_r \theta^* - \beta^*) \quad (5a)$$

$$\ddot{\beta}^* = \Pi_e (J_r \theta^* - \beta^*) - \Pi_g \beta^* - \Pi_d \dot{\beta}^*, \quad (5b)$$

where the resulting four non-dimensional numbers are defined in Table (1).

The initial conditions in non-dimensional form are

$$\theta^*|_{t^*=0} = 0 \text{ and } \dot{\theta}^*|_{t^*=0} = 0 \quad (6a)$$

$$\beta^*|_{t^*=0} = 0 \text{ and } \dot{\beta}^*|_{t^*=0} = 0. \quad (6b)$$

Following the description above, the physics model takes the instantaneous torque and axis revolution as inputs and computes the machine's vibration as output. The laser-measured vibration is related to the solution of Eqs. (5) and (6) by $d_3 = (J_b/J_p)\theta^*w_l/2$, where d_3 is the distance to the bearing holder measured by Laser 3 and w_l is the horizontal distance between the two lasers (Figure 1).

As a nonlinear dynamical system, the MSVT is highly sensitive to operating conditions. As shown in Figure 4 a, b, substantially different vibration responses can occur under identical nominal conditions. This variation reflects evolving system dynamics due to wear, lubricant degradation, and changing lubrication conditions, which cannot be fully captured by fixed model parameters. The objective of the Bayesian inference, described below, is the correction of non-dimensional parameters ($\Pi_e, \Pi_v, \Pi_g, \Pi_d$).

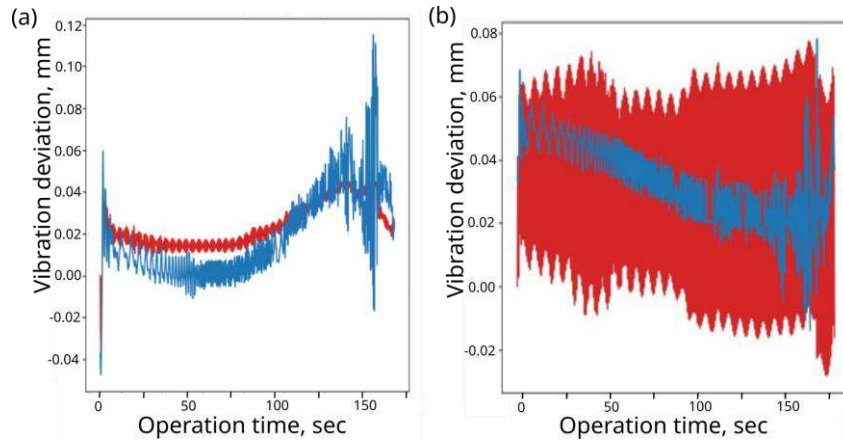


Figure 4: Comparison of experimental (blue) and modelled (red) vibration responses for two independent test runs recorded after 8 hours (a) and 14 hours (b) of machine operation. The experimental signal corresponds to parameter d_3 (see Figure 3), which is measured using Laser 3 (see Figure 1, b).

3.2. Physics-surrogate model

The physics-surrogate model is constructed using the PySINDy library developed by de Silva et al. [24]. Two variants are considered based on linear and nonlinear ordinary differential equations (ODEs). Both use

sparse identification of dynamical systems, representing the system dynamics as a sparse combination of candidate functions, typically polynomial terms [24]:

$$\dot{\mathbf{X}} = \mathbf{W} [F_i] \quad (7)$$

where $\mathbf{X}$ is the state vector, $[F_i]$ is the vector of functions F_i , in which each F_i describes linear/non-linear mutual relations between states in $\mathbf{X}$, $\mathbf{W}$ is a weighting that characterizes the impact of each term F_i on system dynamics. The state vector in our study $\mathbf{X} = [T, V, R]$, where T is torque, V are vibrations, R are axis revolutions (see examples of these characteristics in Figure 2, a, b, c). The optimization of Eq. (7) discussed in the next section aims to estimate weights $\mathbf{W}$ that best fit states $\mathbf{X}$ to the set of terms F_i [24].

Table 2. Preset terms F_i for vibration surrogate model in accordance with Eq. (7)

$$F_1 = V; F_2 = T; F_3 = R; F_4 = V^2; F_5 = V * R; F_6 = T * R; F_7 = R^2; F_8 = T * R^2; F_9 = T^2 * V$$

the variables are: T - torque, V - vibrations, R - axis revolutions

The physics-surrogate model accuracy depends on the selected candidate terms F_i in Eq. (7), which may not fully capture the underlying system dynamics. The terms were selected empirically to represent the average vibration behavior while minimizing approximation error and maintaining a compact model. The final set is given in Table 2. Higher-order nonlinear terms were also tested but provided no significant improvement and were excluded.

Like the physics-based model, the physics-surrogate model was adapted to evolving system dynamics through Bayesian inference at each test run. The coefficients $\mathbf{W}$ associated with the basis functions F_i in Eq. (7) were updated using measured vibrations, torque, and shaft speed. These coefficients define the parameter space for the NO, which forecasts their temporal evolution rather than the vibration signals directly. An example of the resulting vibration reconstruction is shown in Figure 5, a.

Some alternative approaches for physics surrogate models design should be mentioned, particularly based on stochastic differential (SDE) [21, 23] and neural differential (NDE) [22] equations. Within the proposed framework, these approaches are alternatives that could be incorporated in the same manner as the ODE-based surrogates considered here.

We also note the SDE approach [21,23], which naturally incorporates uncertainty into system identification. This provides model-confidence and predictive-reliability estimates, particularly valuable for closed-loop control and decision-making in vibration analysis. In this study, uncertainty is introduced through Bayesian inference, using measured torque, vibration, and shaft speed to update the prior parameter distributions.

4. Models' parameters estimates and vibration forecasting

As discussed above, both physics-based and physics-surrogate models (Section 3) become inaccurate as the system dynamics evolve between successive test runs, leading to discrepancies between forecasts and measured responses (Figure 3, b). To account for this evolution, the model parameters are updated independently for each test run using Bayesian inference of the measured responses. For the physics-based model (Section 3.1) this update applied to parameter set is $\varepsilon_i = \{\Pi_e, \Pi_v, \Pi_g, \Pi_d\}$, while for the physics-surrogate model (Section 3.2), it is $\varepsilon_i = \mathbf{W}$ (see Eq. (7)).

4.1. Bayesian inference for parameters update

Two approaches for updating the model parameters were investigated: classical Bayesian [30] and deep Bayesian [33,34] optimizations. A brief description in the context of the proposed framework is given below, however detailed theoretical and implementation aspects are provided in [29].

For each test run, the physics-based and physics-surrogate models are treated as black-box functions of the measured torque (T) and shaft speed (R). Candidate parameter sets $\{\Pi_e, \Pi_v, \Pi_g, \Pi_d\}$ and $\mathbf{W}$ are evaluated by comparing the corresponding model response V_{mod} with the measured vibration V_{exp} using the squared error metric: $\mathcal{D}_{SE} = \sum_j (V_{mod} - V_{exp})^2$. Parameter sets producing smaller errors are assigned to higher probability.

In classical Bayesian optimization, a Gaussian-process surrogate is used to represent the probabilistic relationship between the model parameters and the observed error. An acquisition function then guides the selection of new parameter configurations by balancing exploration of uncertain regions with exploitation of promising solutions. In this study, the Expected Improvement (EI) criterion is used, as it accounts for both the probability and magnitude of improvement. The resulting parameter distribution is updated for each test run, and its mean is used to update the model parameters.

In deep Bayesian optimization ML is involved to approximate the relevant probability distributions [34,35]. It is particularly suited to highly nonlinear problems and sparse evaluations. Although the present application does not require many evaluations, this approach was investigated because of its potential to infer posterior distributions from limited condition-monitoring data. The implementation was developed using the frameworks of Nogueira and Nielen et al. [31,32], incorporating the deep Bayesian optimization approach of Jankowiak et al. [35].

Importantly, Bayesian optimization provides a probability distribution over the parameter space rather than a single deterministic solution. In this study, the mean of the inferred distribution is used to update the parameters of both the physics-based and physics-surrogate models.

4.2. Neural operator vibrations forecasting

The ML component of the proposed framework uses the parameters of the physics-based and physics-surrogate models to forecast vibration dynamics. Neural operators (NOs) are employed because they learn mappings between functional spaces. Rather than predicting vibration signals directly, the NO forecasts the temporal evolution of the model parameters, reducing the forecasting problem to a low-dimensional parameter space while preserving physical interpretability and enabling reconstruction of the corresponding vibration response.

Similar to conventional neural networks, NOs combine linear transformations with nonlinear activation functions. However, the linear transformations are replaced by integral operators acting on functions [36–38]: $\int k(\xi_{in}, \xi_{out}) a(\xi_{in}) d\xi_{in} \sim \sum_{i=1}^N k(\xi_{out}, \xi_{in i}) a(\xi_{in i}) \Delta \xi_{in i}$, where ξ_{in} and ξ_{out} denote the input and output coordinates, $k(\cdot)$ is the integral kernel, and $a(\cdot)$ is the layer function. Gaussian Error Linear Unit (GeLU) activations

are used following [36]. An important advantage of NOs is their ability to operate across different discretization's of the underlying domain. This allows the learned operator to reconstruct system responses at resolutions different from those used during training, supporting vibration prediction between individual test runs and reducing the need for densely sampled experimental data. The implementation is based on the Python libraries of Kossaifi et al. [37] and Kovachki et al. [38]. Further details on neural operator architectures and discretization properties are provided in [36].

4.3. Processing pipeline.

The complete processing pipeline is summarized in Figure 5. First, a test run temporarily interrupts normal operation, during which shaft speed (R) follows a Stribeck-ramp profile while torque (T) and vibration (V) are measured synchronously. These measurements are used to update the model parameters through the Bayesian inference procedure described in Section 4.1.

The updated parameters are then provided to NO, which forecasts their evolution over the prediction

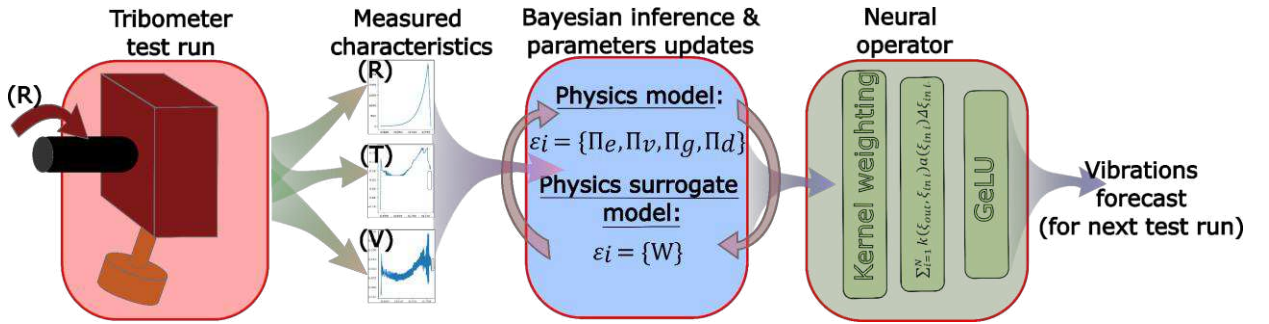


Figure 5. Schematics of the experimental pipeline for forecasting of the future vibration states. The vertical arrows in parameters update block (blue) denote the optimization loop. Notions (R) , (T) , (V) are consistent with the rest paper and correspond to axes revolutions, torque and vibrations correspondently.

horizon defined by the interval between consecutive test run. The predicted parameters are subsequently used in the dynamical model to reconstruct the future vibration response. Thus, forecasting is performed in the low-dimensional model-parameter space, while vibration signals are obtained as model outputs. The framework operated the same with physics-based and physics-surrogate models, following the same pipeline.

5. Discussion.

The results are based on six full experimental campaigns, each comprising approximately 29–38 consecutive test runs. Representative vibration signals are shown in Figure 7a. Five campaigns exhibited distinct vibration-evolution patterns, while one progressed to failure. The framework was trained on one non-failure campaign and evaluated on the remaining four; the failure case is discussed separately.

All computations were performed on a workstation with an Intel i7 processor and 32 GB RAM, without GPU acceleration. To reduce computational cost, torque, shaft speed, and vibration signals were down sampled to 1,000 points before processing, compared with approximately 360,000 samples in the original 2 kHz recordings.

This reduction substantially decreased computational time while preserving prediction accuracy. Further reductions caused noticeable accuracy degradation, indicating that 1,000 points provide a suitable balance between computational efficiency and information retention.

5.1. Parameters updates and vibration dynamics of the system.

Before presenting the forecasting results, Figure 6 illustrates the effect of parameter updating. Figure 6, a, compares the measured vibration (blue) with the physics-based model response using the initial parameters (red), showing a clear discrepancy due to evolving system dynamics. After Bayesian optimization, the agreement improves substantially (Figure 6, b), demonstrating the effectiveness of the update procedure.

The optimization convergence is shown in Figure 6, c, through the squared-error metric $\mathcal{D}_{SE}$. Classical Bayesian optimization required approximately eight iterations on average and was terminated when $\mathcal{D}_{SE}$ fell below a predefined threshold. The green marker indicates the selected final parameter set.

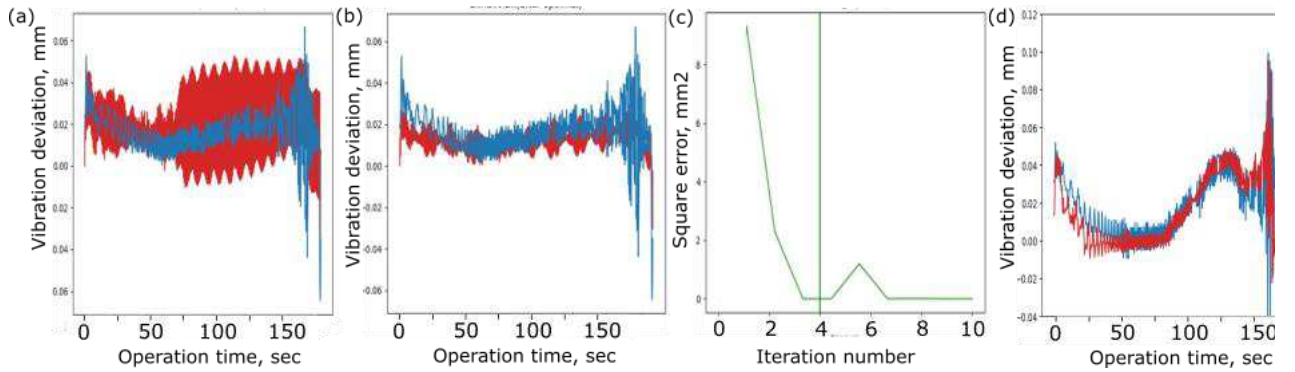


Figure 6. The model parameter updates using Bayesian optimization: (a) vibrations modeled using physics model with preset parameters (red) and vibrations measured during a test run (blue); (b) vibrations modeled after Bayesian optimization (red) and measured during a test run (blue) for the same case as in (a); (c) evolution of the squared-error metric $\mathcal{D}_{SE}$ during classical Bayesian optimization, where green marks the selected parameter set ε_i with minimum $\mathcal{D}_{SE}$ achieved; (d) vibrations modeled using physics surrogate model after optimization (red) and measured during a test run (blue).

Deep Bayesian optimization achieved comparable results (Figure 6, d) but required substantially more iterations—up to approximately 100 on average—to accumulate sufficient statistics. Consequently, its computational time increased from approximately 9 s for classical Bayesian optimization to 300–450 s the deep version.

Figure 6, d, shows the measured (blue) and modeled (red) vibrations from the physics-surrogate model using the same procedure as Figure 6, a–c. The surrogate model generally provides a better fit, likely due to the selected basis functions (Section 3.2).

Figure 7 illustrates the system dynamics over successive test runs. In Figure 7a, the vibration responses from a non-failure campaign are arranged chronologically, with runs separated by green lines. The response progressively drifts from its initial balanced state, as highlighted by the red sliding-average curve obtained using a Savitzky–Golay filter.

The figure also reveals that high-speed operation produces distinct vibration peaks near the end of each test run. These peaks are initially larger but decrease as the test progresses. Overall, the substantial difference between the first and final test runs confirms the evolution of system dynamics. The rate of vibration change

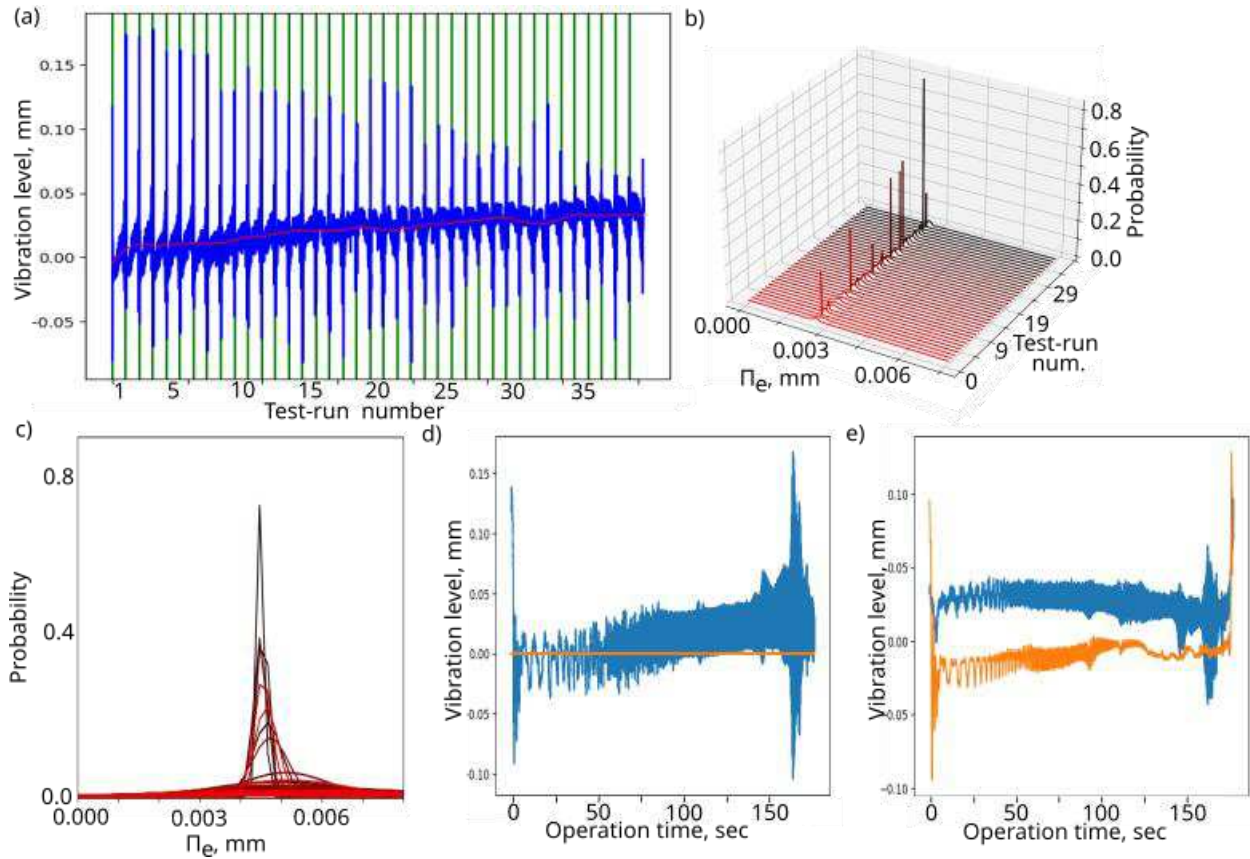


Figure 7. (a) Vibrations from several test-runs during machine operation; (b) distributions of parameter P_1 evolution during test-runs; (c) 2D profile of distributions from (b); (d) example of vibrations forecasting using training without additional regularization terms; (e) example of vibrations forecasting using PINNs regularization. In (b) and (c) the color encodes the number of test-run, where red and black defines the first and last ones. In (d) and (e) the forecasted and measured values are marked with orange and blue correspondently.

is highest during the early stages and gradually decreases during later operation.

The observed reduction in vibration gradients and peak amplitudes may result from a redistribution of vibrational energy across a broader frequency range, potentially caused by wear-induced changes in the system's mechanical properties. A detailed frequency-domain analysis, however, is beyond the scope of this study.

Figures 7, b, c, illustrate the corresponding parameter updates. As an example, the posterior distributions of parameter Π_e , obtained through classical Bayesian optimization for the test runs in Figure 7, a, are shown. The posterior mean gradually shifts from higher to lower values, while the variance decreases over the course of the experiment. The decreasing variance indicates increasing confidence in the parameter estimates and reflects the improved agreement between modelled and measured vibrations. This may be related to the model's limited ability to reproduce the sharp gradients and pronounced peaks observed during the early test runs. As the vibration response becomes smoother, the model provides a better representation of the system

dynamics, resulting in more concentrated posterior distributions. The evolution of these posterior distributions therefore captures both changes in system dynamics and the model's predictive capability. In the following subsection, this behaviour is further exploited to detect failures not represented in the training data.

5.2. Forecasting results.

The results of the proposed framework are summarized in Table 3. The framework was trained on one non-failure campaign and evaluated on the remaining four, with results averaging across the five campaigns. Performance is measured using the relative mean difference: $\mathcal{D}_{md} = 1/N \sum_{i=1, \dots, N} (y_{forecast\ i} - y_{exp\ i}) / y_{exp\ i}$, where (N=1000) is the number of down sampled points, $y_{forecast}$ is the reconstructed vibration response from the forecast model parameters, and y_{exp} is the corresponding measured signal.

The proposed framework is compared with three conventional ML models: a fully connected neural network (fNN), convolutional neural network (CNN) and ResNet. These models directly forecast vibration signals using either standard training ("No regularization") or physics-informed training with model-based regularization, following the PINN formulation in [4]. The latter uses the updated model parameters for each test run. A third setting ("ODE") uses linear ODEs identified with PySINDy [24] as regularization, demonstrating the importance of nonlinear modeling for this application.

As shown in Table 3, the proposed framework consistently outperforms the conventional ML approaches. Standard training and linear-ODE regularization yield the lowest accuracy, while the typical forecast behavior is illustrated in Figure 7, d, where the measured vibration (blue) is compared with the ML forecast (orange).

Poor performance without regularization is mainly attributed to overfitting, while linear ODE regularization is limited by its inability to capture high complexity of nonlinear dynamics. Both approaches also suffer from the limited representativeness of a single training campaign. Performance is expected to improve with larger and more diverse datasets.

Table 3. Quantitatively forecasts error rates as a relative absolute mean difference (over all test-runs)

<i>ML model</i>	<i>No regularization</i>	<i>ODE</i>	<i>Physics model</i>	<i>Physics surrogate model</i>
Neural operator	-	-	24%±12%	16%±8%
fNN	46%±26%	54%±26%	32%±19%	36%±18%
CNN	51%±19%	49%±25%	29%±18%	31%±21%
ResNet	36%±23%	47%±32%	36%±19%	28%±16%

Nonlinear physics-based and physics-surrogate regularization modestly improves forecasting accuracy (Table 3) by better capturing the Stribeck-ramp response (Figure 7, e). However, errors increase at higher shaft speeds due to more complex vibration dynamics.

The proposed framework achieved the best forecasting performance among the evaluated methods. The physics-surrogate model also outperformed the physics-based model in this case, likely due to the selected basis functions in Eq. (7), while the lower performance of the physics model may reflect unmodeled phenomena

or simplifying assumptions. However, because the basis-function selection is empirical, this result should be considered case-specific rather than evidence of a general advantage of surrogate models.

Representative forecasts are shown in Figure 8 a, b. Although the framework provides superior accuracy, errors remain due to inaccuracies in both the NO and underlying models. The physics model mainly struggles to reproduce the sharp vibration increases during the initial test runs, while the surrogate model shows greater amplitude deviations. Both models exhibit larger errors at the beginning of the sequence, where the vibration trends are less distinct and the underlying dynamics are therefore more difficult to identify.

Overall, the proposed framework achieved superior performance on the investigated dataset. Although larger datasets and deeper neural networks may favor conventional deep-learning approaches, industrial applications often face limited and costly data availability. In such settings, the proposed framework offers a viable alternative by leveraging physics-based and physics-surrogate models to reduce data requirements and dependence on complex ML architectures.

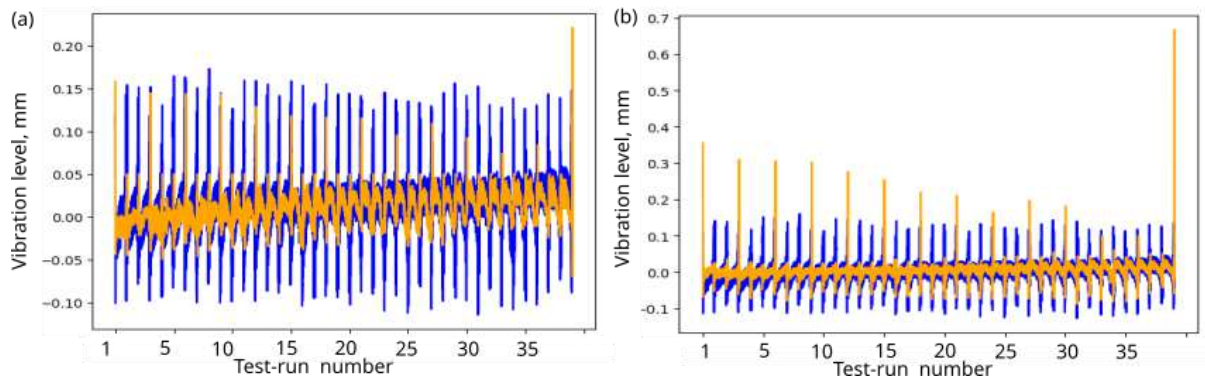


Figure 8. Results of forecasting vibrations using NO and models reconstruction (orange) versus real characteristics (blue) for: (a) physics model, (b) physics surrogate model.

5.3. Performance of the framework for failure case

A special case considers training the framework exclusively on non-failure data and testing it on a failure campaign. This scenario reflects practical applications where failure data are costly, hazardous, or impossible to obtain solely for ML training.

Figure 9 shows the measured and forecasted vibration responses. Failure onset is marked by an abrupt increase in vibration deviations, indicated by the red vertical line, likely caused by bearing damage and the resulting loss of contact and delayed load transfer. Forecast accuracy during the early test runs is comparable to that reported in Table 3; however, it decreases after failure onset to $(28\pm 14\%)$ for the physics-based model and $26\pm 13\%$ for the physics-surrogate model. The main source of error is a mismatch in vibration amplitudes, with the framework generally predicting lower levels than those observed during failure. Despite

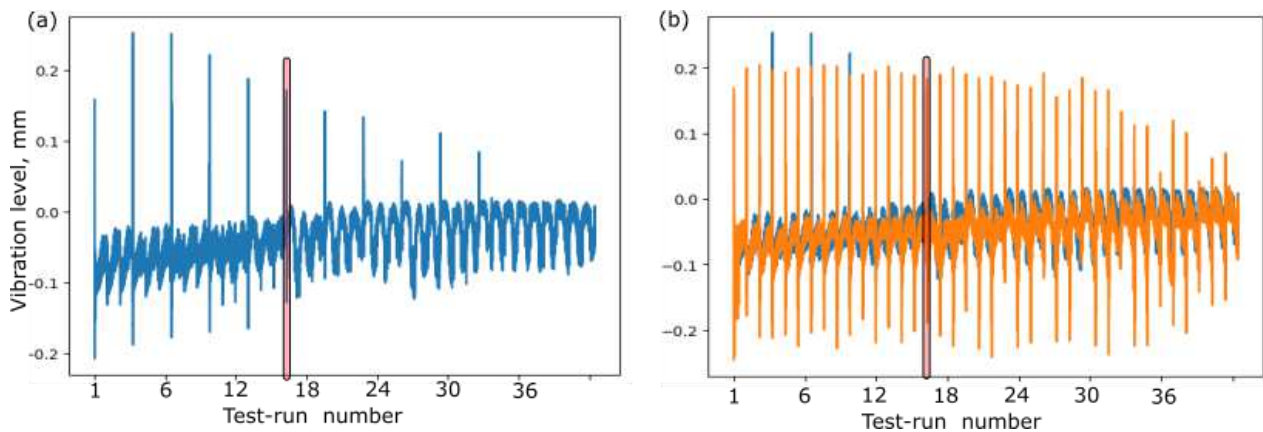


Figure 9. A sequence of test runs for failure experimental campaign, with vertical marker indicating the failure start: (a) measured vibrations, (b) reference of forecasted vibrations (orange) to measured ones (blue).

this degradation, the framework continues to capture the overall vibration dynamics, demonstrating its potential for forecasting previously unseen failure conditions.

Conclusion

This work presents a physics-informed ML framework for vibration forecasting in self-lubricated journal bearings. Physics-based and surrogate models are continuously updated using measured data, while a neural operator forecasts their parameter evolution over 1–8 h horizons. The predicted parameters are then used to reconstruct future vibration responses.

Despite irregular forecasting intervals, the framework provides reliable predictions and outperforms conventional signal-based ML approaches on the investigated data. Forecasting in parameter space reduces the need for large training datasets and provides greater robustness to nonlinear system behavior. Future work will explore parameter evolution for anomaly detection and the use of low-dimensional representation to generate synthetic vibration data for training augmentation.

The data utilized in this study is available once upon a reasonable request. The code is available as a github repository [29].

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