INL/MIS-23-75144-Revision-0

Physics-informed Data-driven Degradation and Prognostic For Hydropower System

October 2023

Changing the World's Energy Future

Jianqiao Huang, S M Shafiul Alam, Shijia Zhao, Feng Qiu, Murat Yildirim , Spencer Larson, Mucun Sun

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Argonne NATIONAL LABORATORY

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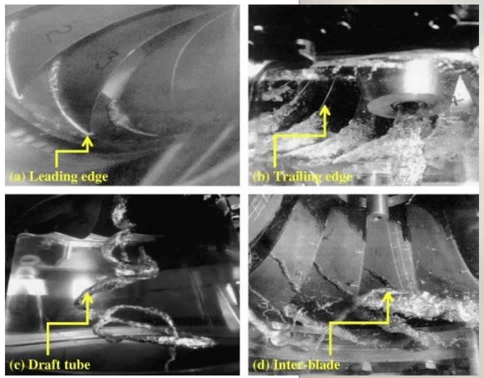
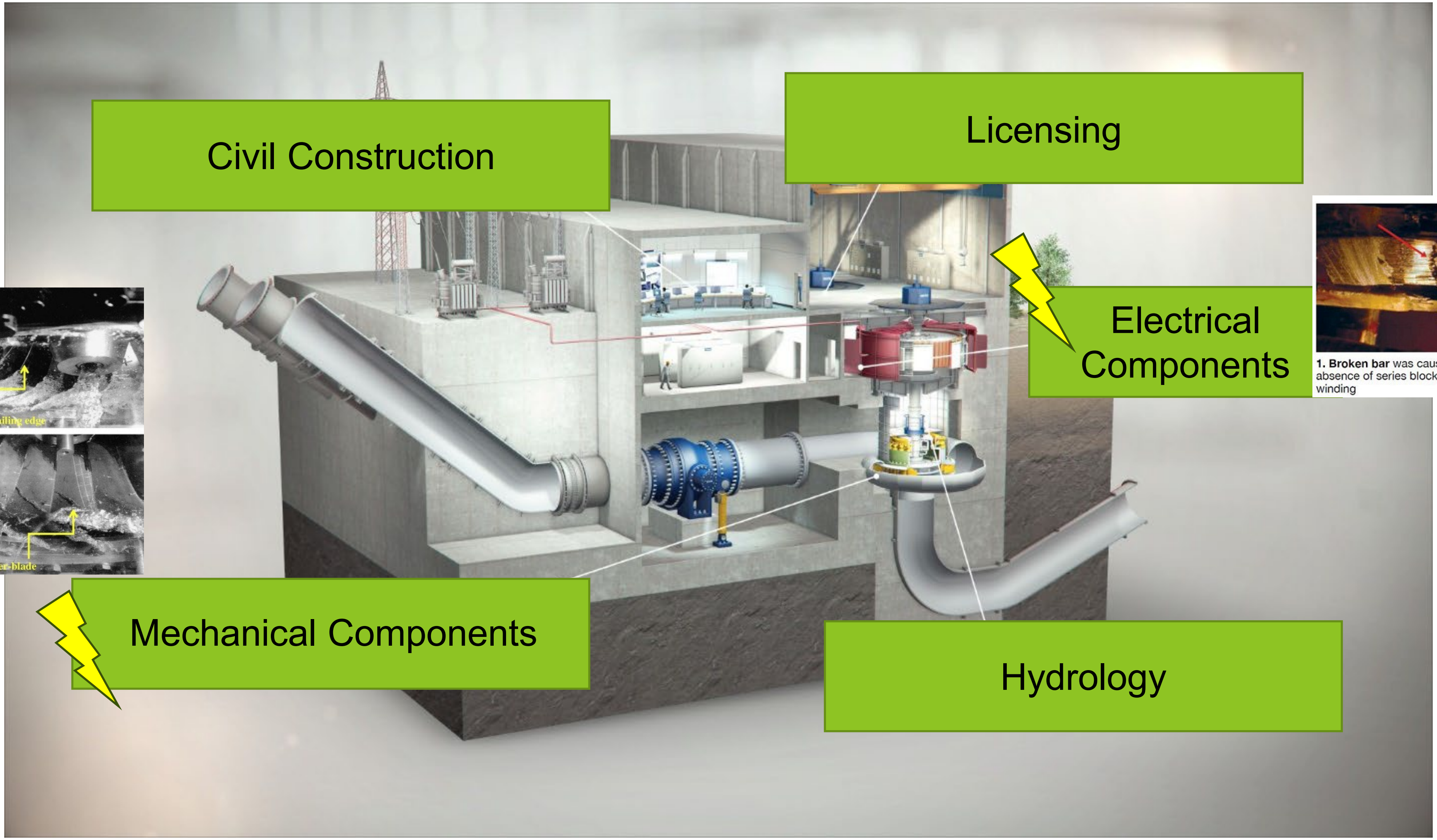
INL Idaho National Laboratory





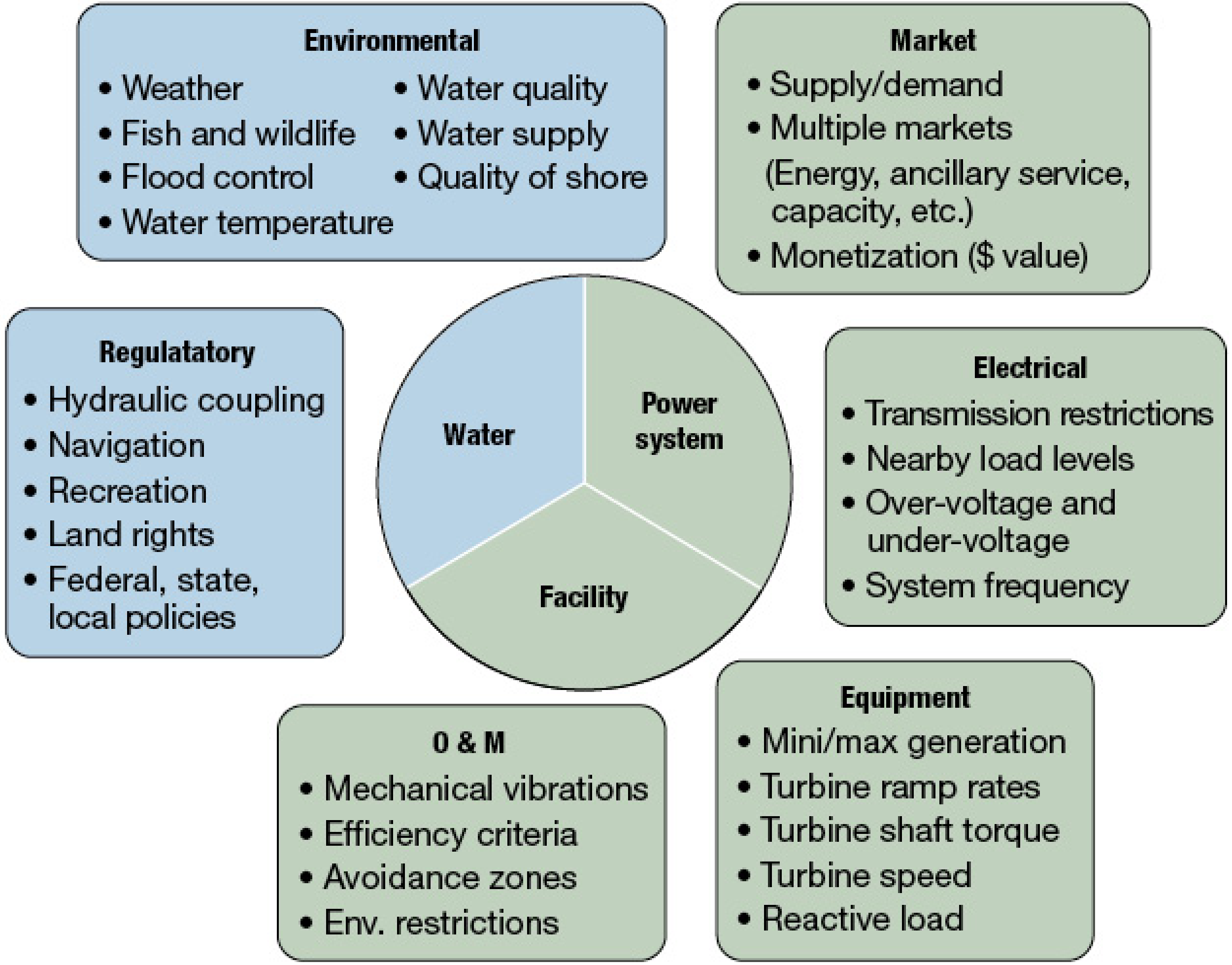
1. Broken bar was caused by absence of series blocking on an end-winding

2. Several inches of copper burned away on a stator bar as a result of endwinding resonance

Image Source: Voith

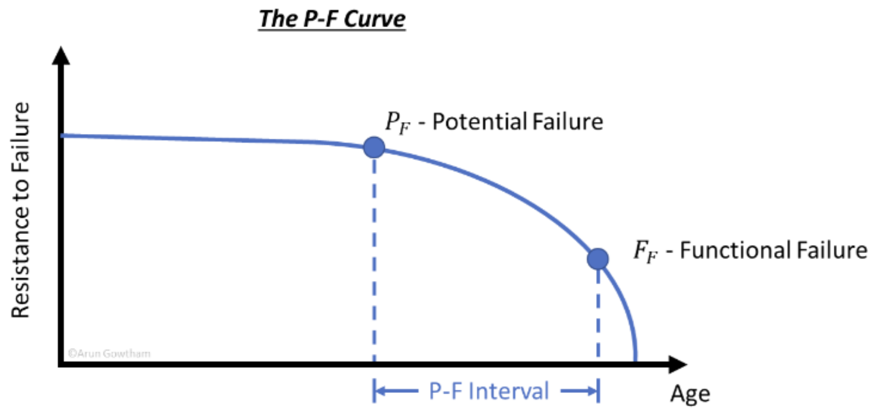
Why hydropower degradation modeling?

- Federal Energy Regulatory Commission (FERC) relicensing
  - Most of hydropower plants overestimate their power potential
- Flexibility operation accelerate degradation
- High Operation and Maintenance (O&M) cost



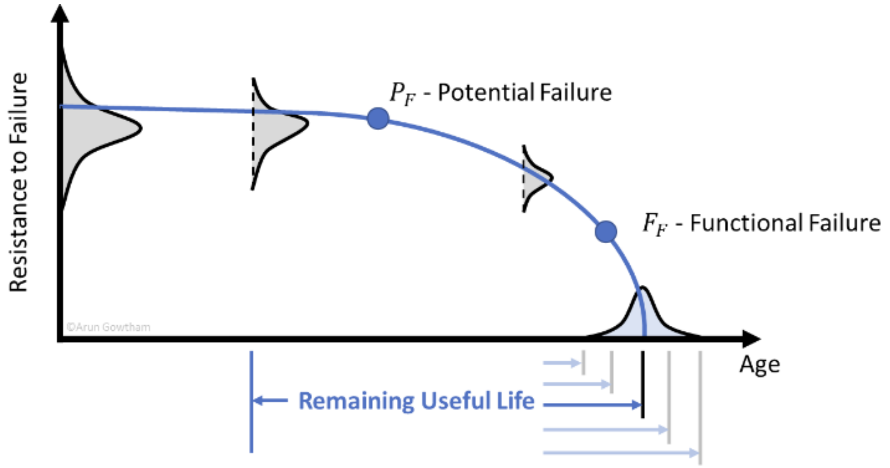
Why prognostic?

- Conventional health monitoring are deterministic
- Forms of prognostic
  - Parametric: distribution functions
  - Non-parametric: Intervals, percentiles
- To date, diagnostic are used in hydro power systems predominantly
- Prognostics are gaining tractions in hydro power systems
  - Situational awareness
  - Stochastic Scheduling and operations
  - Remain useful life (RUL) estimation



RUL through diagnostic

RUL through prognostic



Mechanical Components

- The main mechanical component of interest are the large hydrodynamic bearings that support the unit's drive shaft.
  - These include both radial and thrust bearings.
  - Pressurized oil system provides lubrication and cooling.
  - Sensors monitor bearing temp., oil pressure, oil height, oil temp, and vibration magnitude.

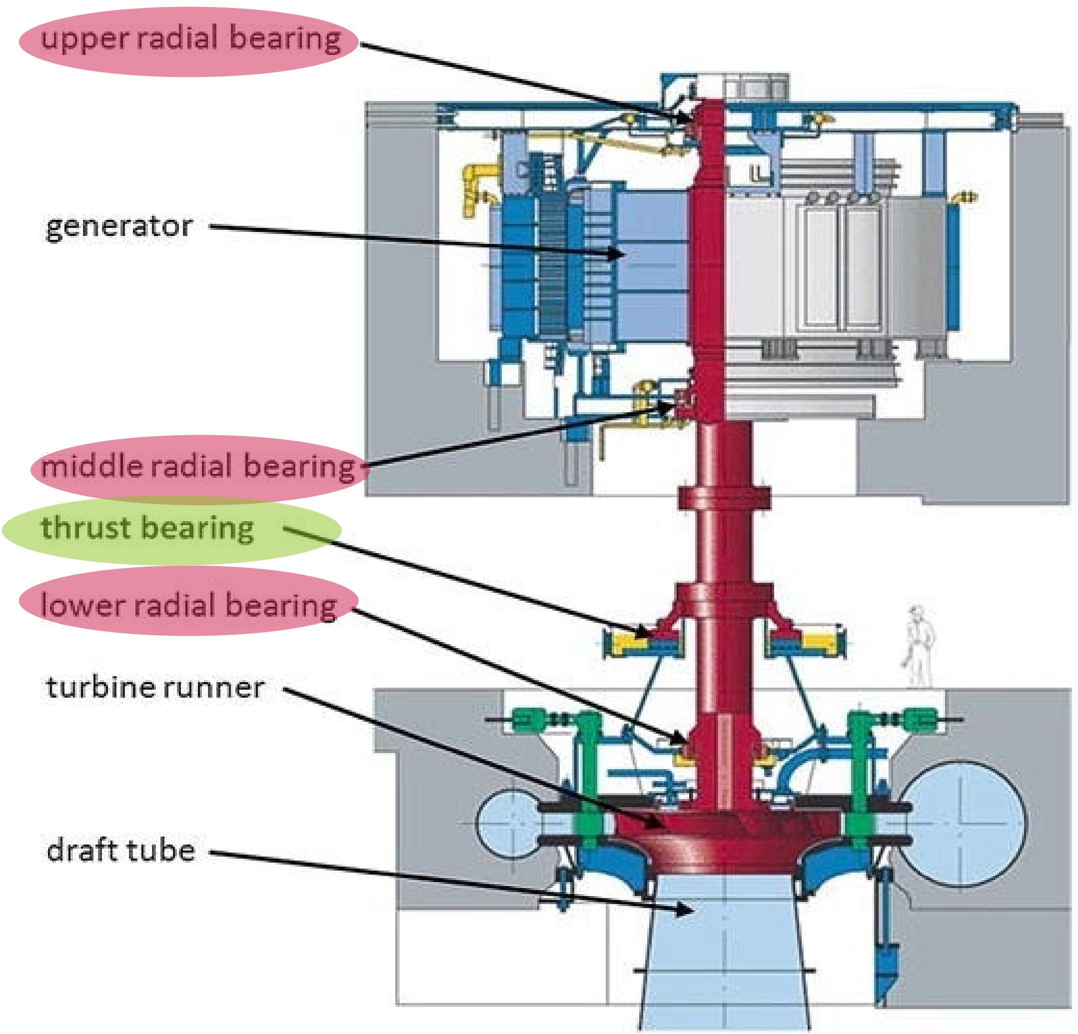


Fig. 1: Vertical Francis hydrogenator unit with bearing locations highlighted. **Image Source:** Wasilczuk et al., "Large Hydrodynamic Thrust Bearings and Their Application in Hydrogenerators", 2013.

Electrical Components

- Power Transformer
- Instrumentation Transformer
- Relay, and Protection Devices
- Generator Stator
- Generator Rotor
- Generator Exciter
- Automatic Voltage Regulator, Power System Stabilizer

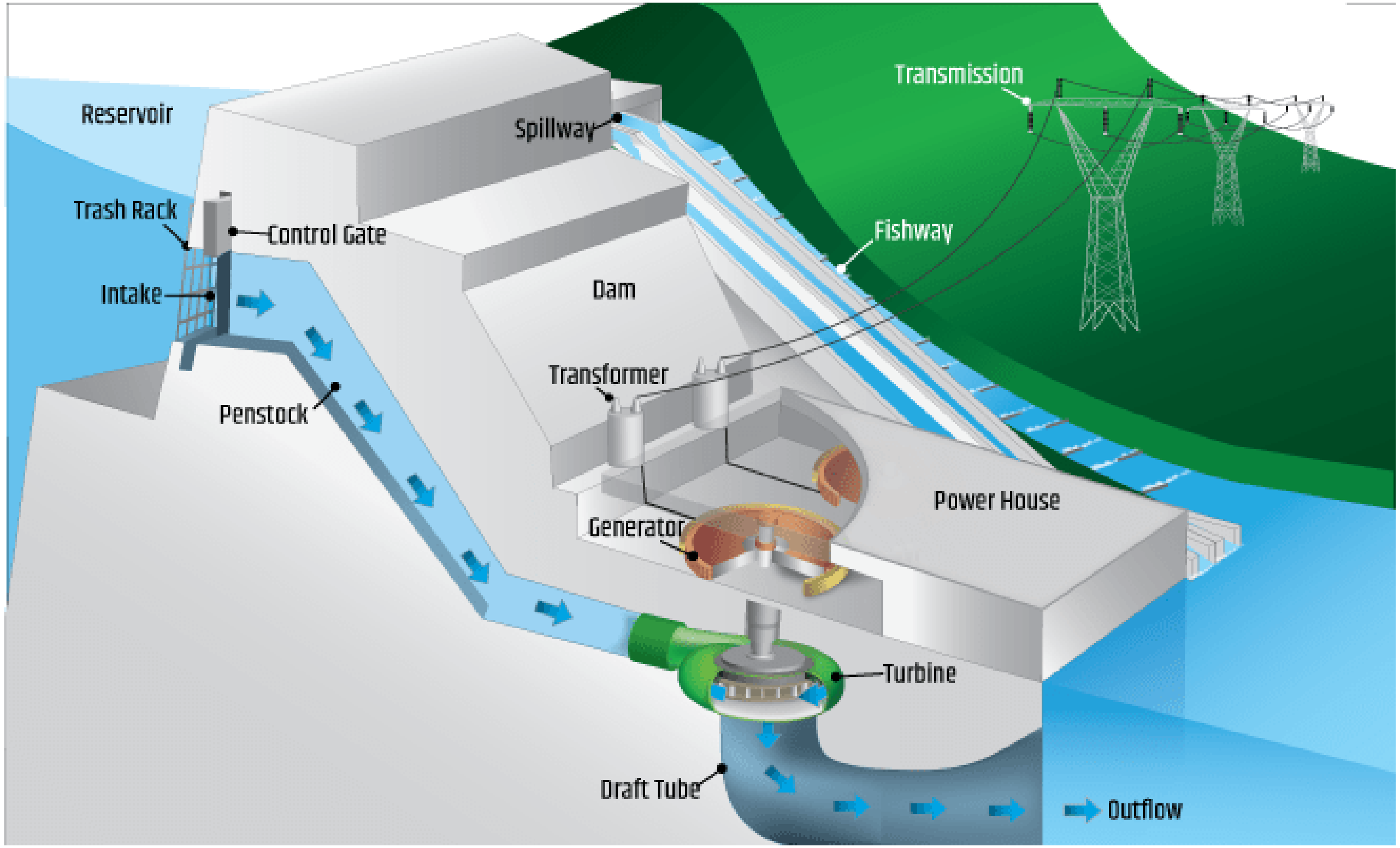


Image Source: WPTO

Two studies

I. Modeling hydropower degradation through vibration signal
II. Physic-informed degradation and prognostic

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I. Modeling hydropower degradation through vibration signal
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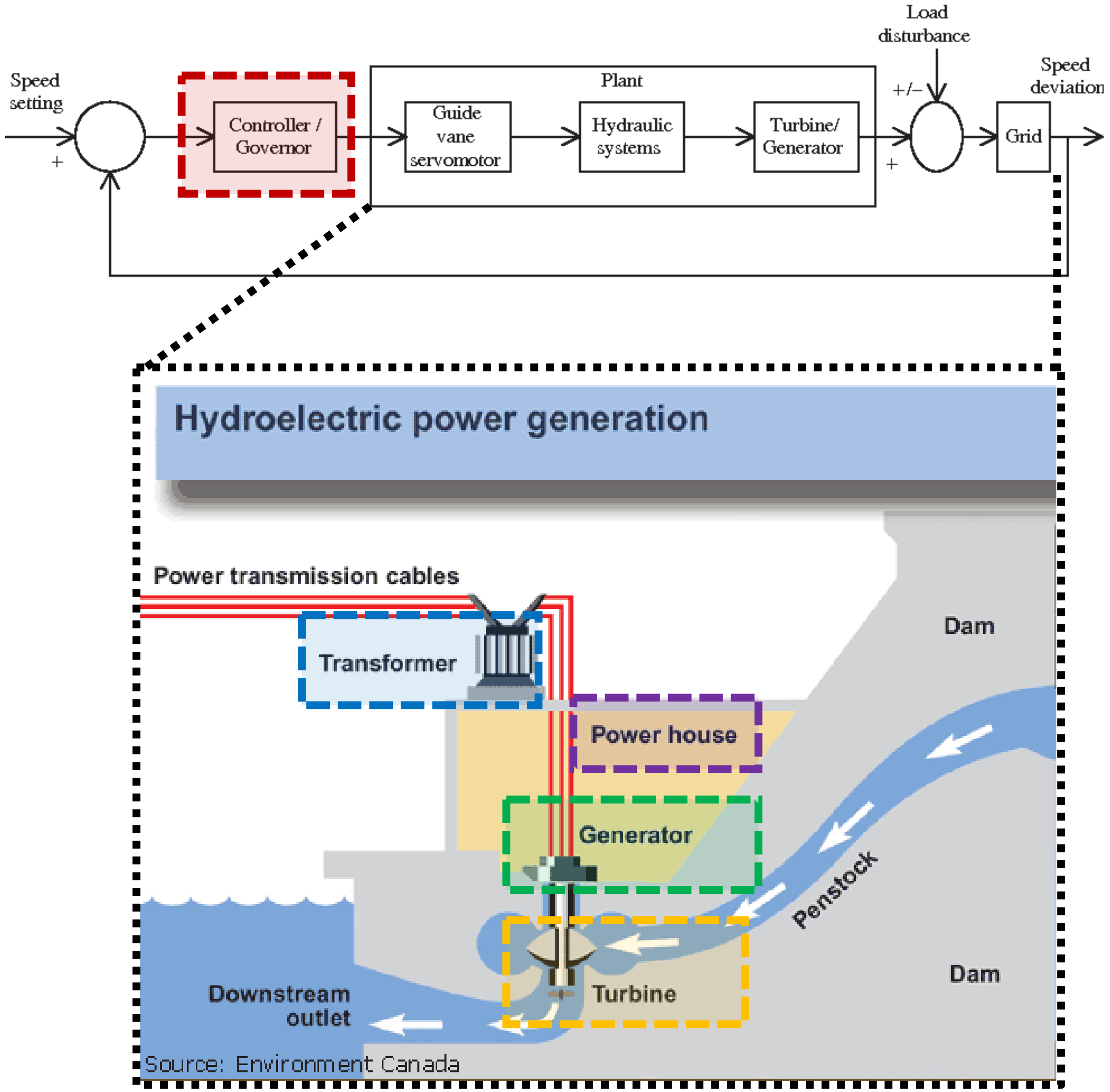
Figurative Overview of Measurements in Hydro Power Generation

- Governor-Distance-Vertical
- Generator-Real-Power
- Generator-Vibration-Horizontal
- Generator-Vibration-Vertical
- Hydraulic-Turbine-Flow
- Hydraulic-Turbine-Vibration-Horizontal
- Hydraulic-Turbine-Vibration-Vertical
- Transformer-Temperature
- Metering-and-Control-Current
- Metering-and-Control-Real-Power



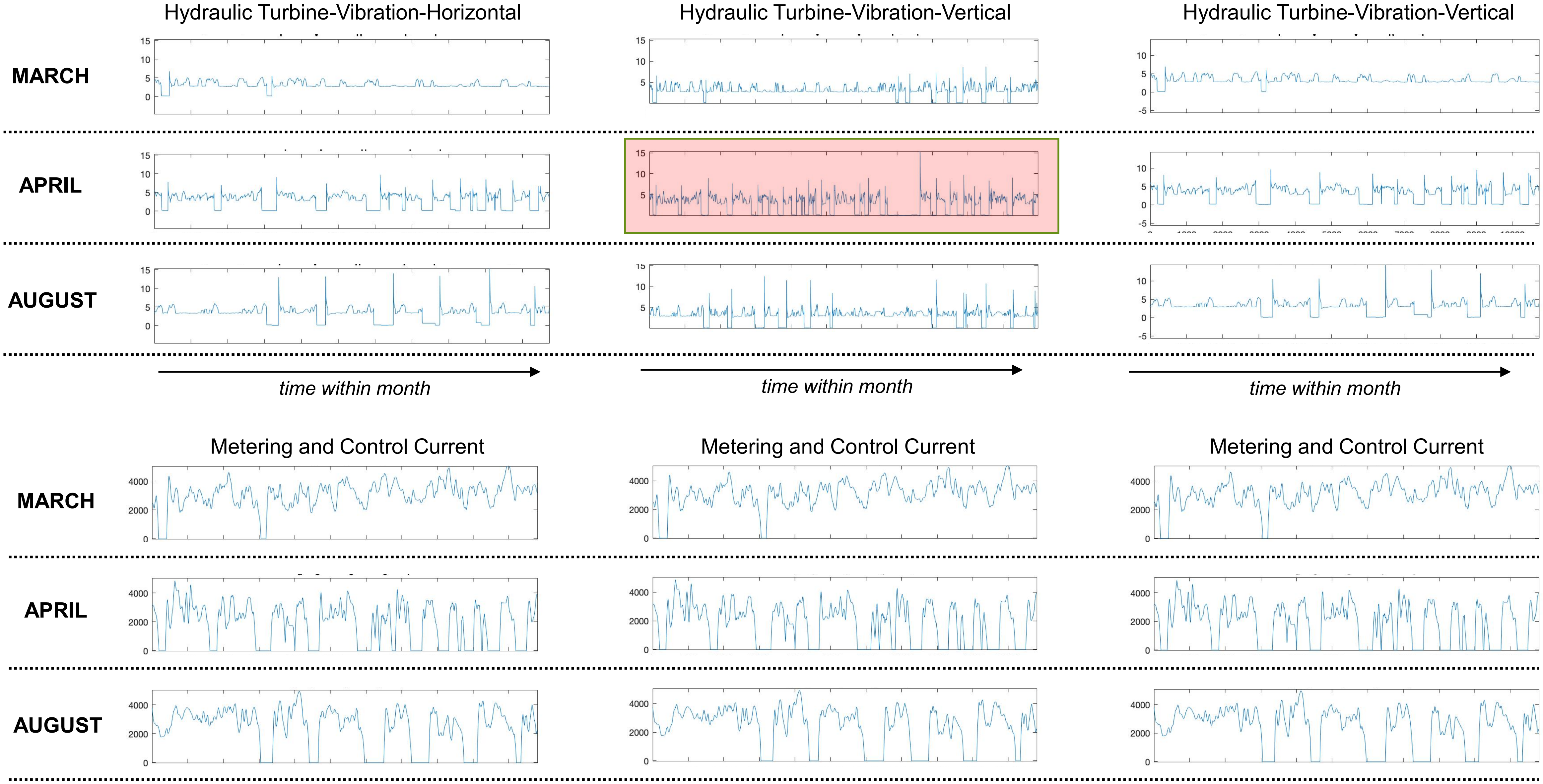
Initial Analysis Summary of Studied Units and Time Periods

Site/Unit	Snapshots of Interest
Site 36922 Unit LO-39	March (No Outage)
	April (Outage)
	August (Outage)
Site 36922 Unit LO-71	January (No Outage)
	July (No Outage)
	September (Outage)
Site 36922 Unit LO-93	January (No outage)
	July (No outage)
	September (Outage)

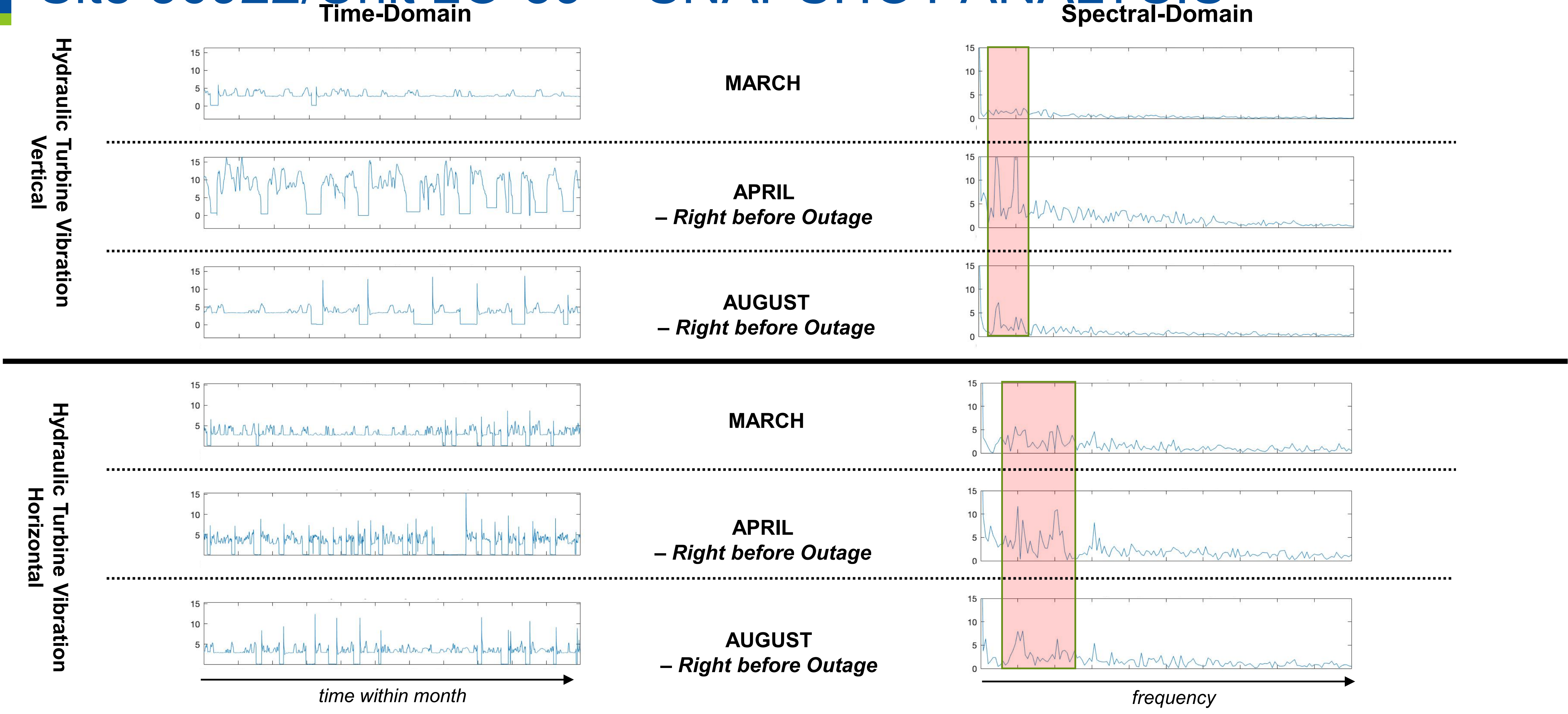
baseline
probable vibration manifested issue
probable periodic maintenance
baseline
baseline
probable vibration manifested issue
baseline
baseline
probable cavitation manifested issue

Main limitation: Lack of access to maintenance records!
Initial approach: Considering long periods of halted production as potential maintenance outages

Site 36922/Unit LO-39 – Representative data



Site 36922/Unit LO-39 – SNAPSHOT ANALYSIS

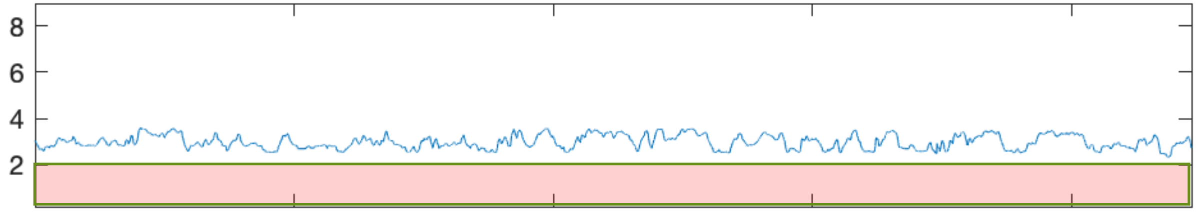


Data suggest that the most likely scenario is that the August outage is periodic, whereas April may be corrective/preemptive. April has significant change in the functional form of vibration, as apparent in spectral domain analysis as well.

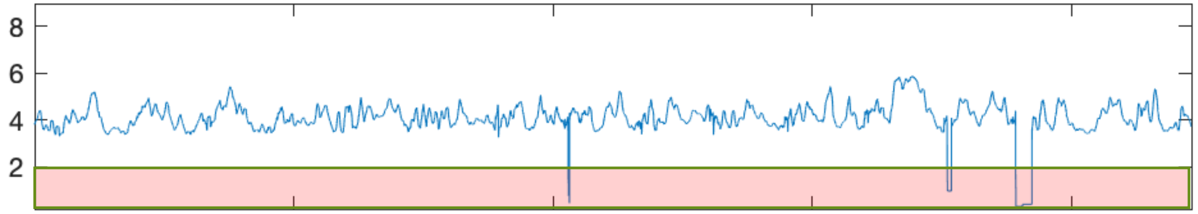
Site 36922/Unit LO-71 – snapshot Analysis

Hydraulic Turbine-Vibration-Horizontal

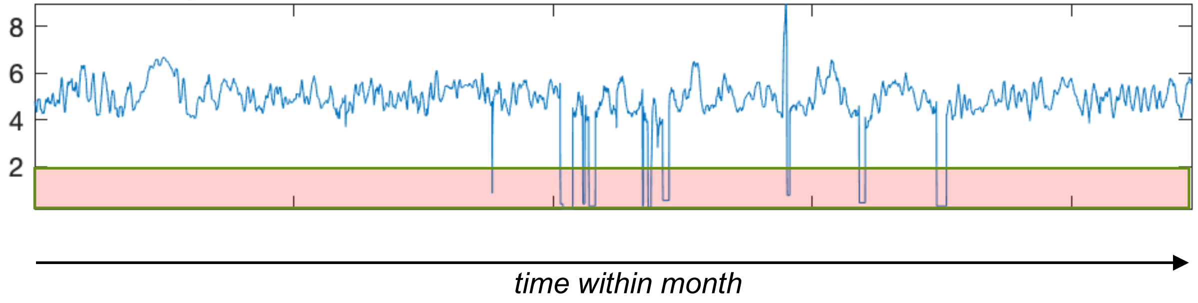
Sensor Readings During January



Sensor Readings During July



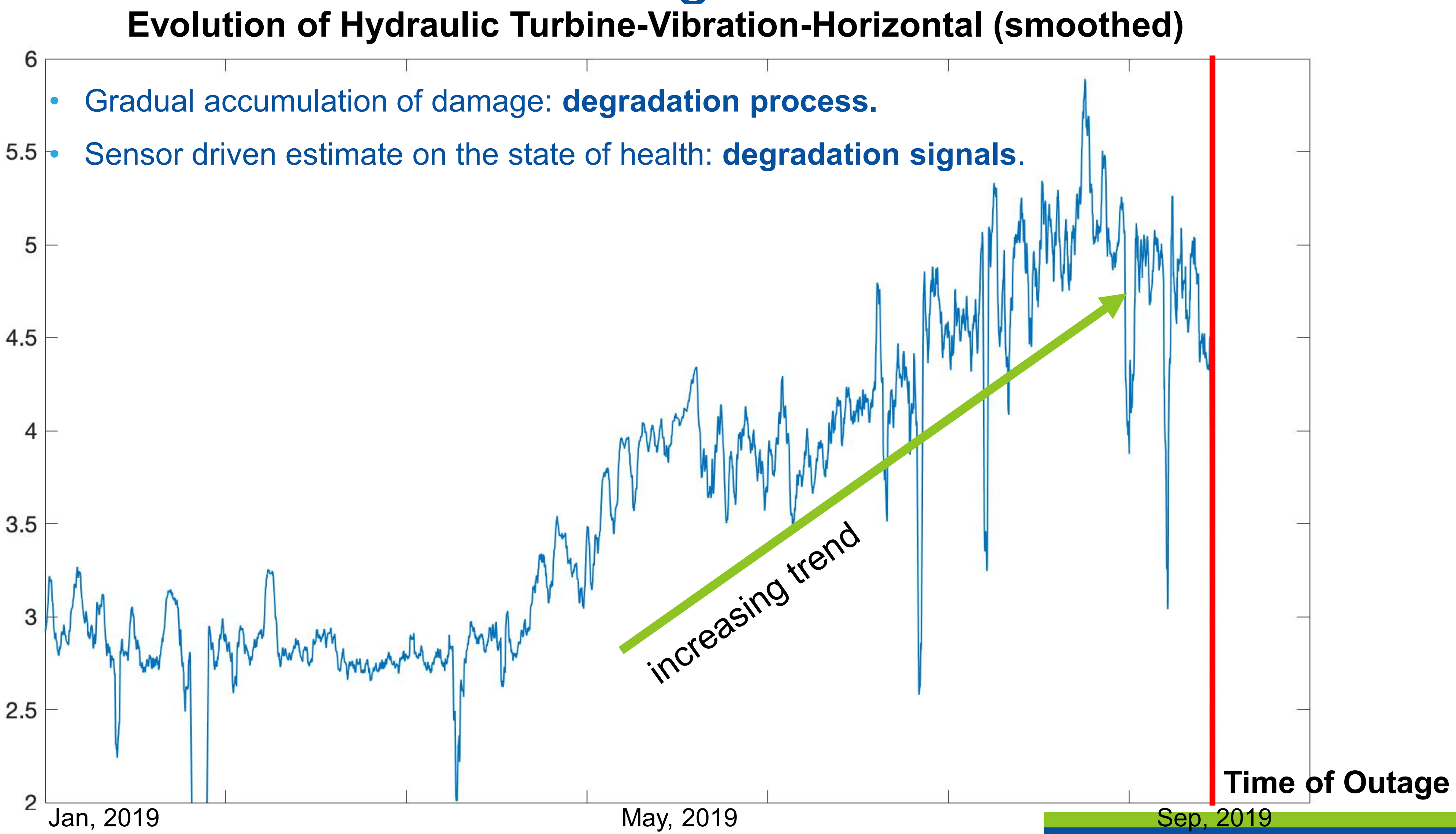
Sensor Readings During September– *Right before Outage*



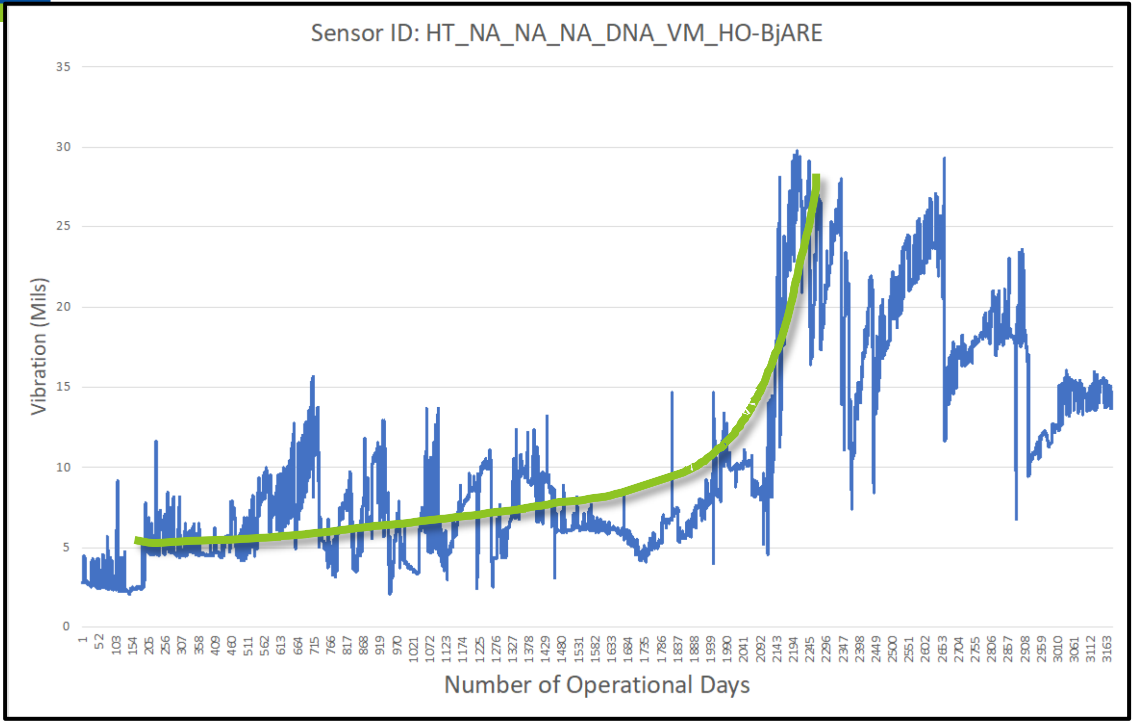
Gradual rise in the number of nonconforming points (dips)

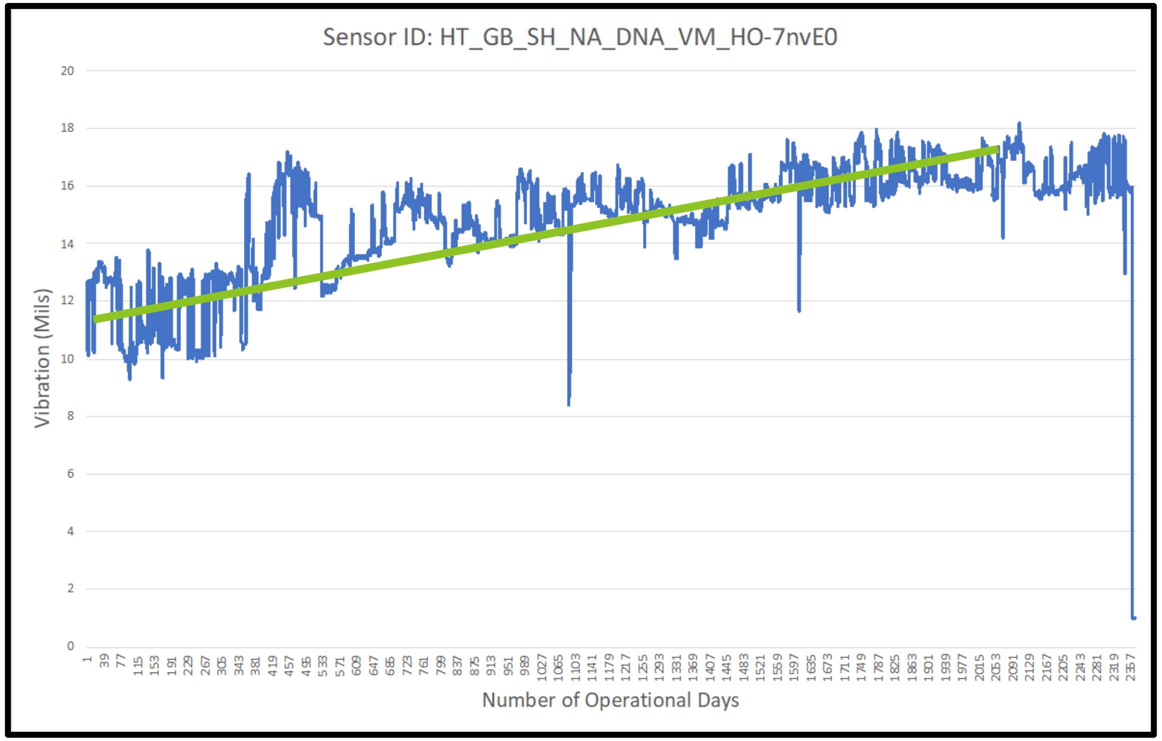
Gradual rise in the average vibration levels

Site 36922/Unit LO-71 – Long-Term Trends



Guide Bearing Degradation





Exponential Degradation Path

Linear Degradation Path

Two models are considered for comparison

Degradation Modeling Summary

1. **Linear Degradation Model**: $S(t) = \theta + \beta \times t + \epsilon(t)$

2. **Exponential Degradation Model**: $S(t) = \exp\left(\theta + \beta \times t + \epsilon(t)\right)$

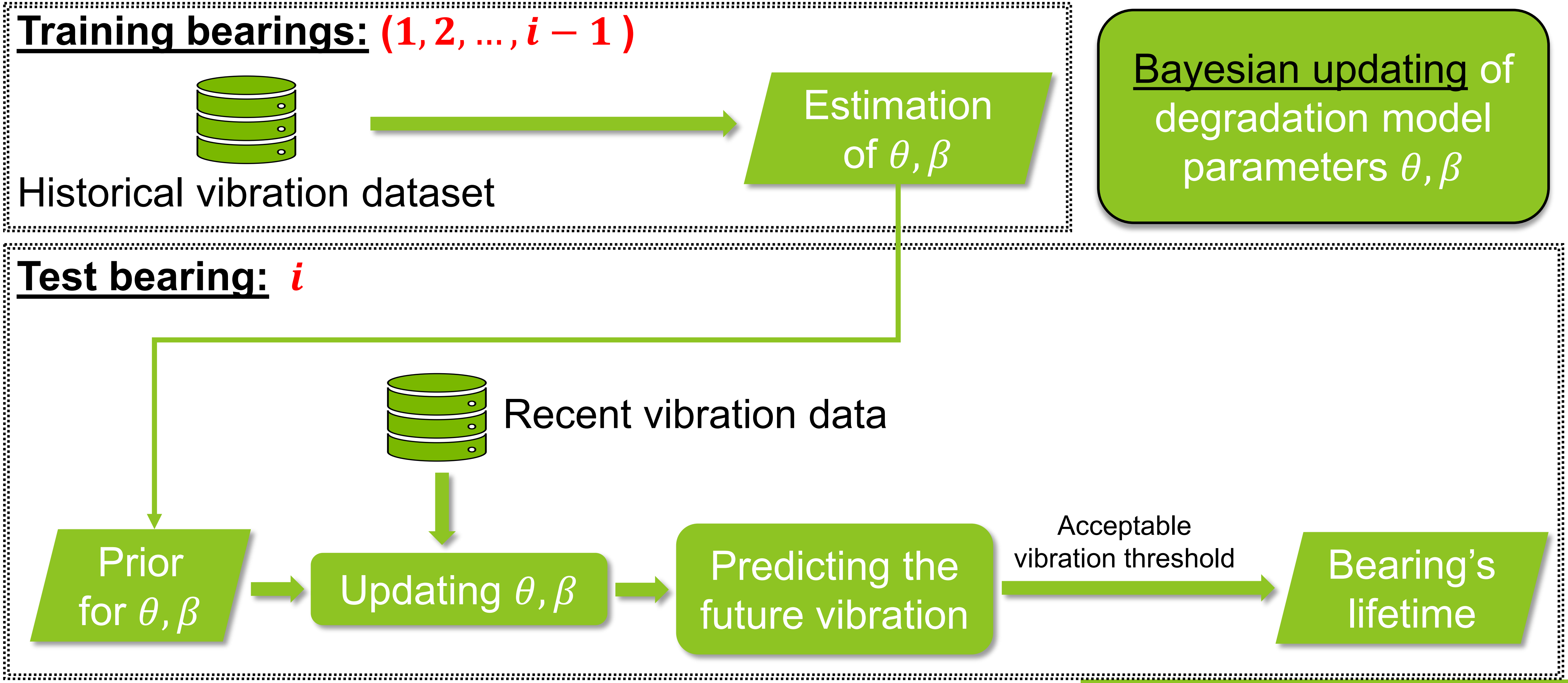
Salient features of these models:

- θ, β are random variables which evolve **incrementally** with data
- $\epsilon(t)$ are Brownian motion error
- Bearing's failure happen when $S(t)$ reaches a threshold D
  - Threshold determined by subject matter experts (SME)
  - Threshold can also be determined by ISO standard for bearing vibrations ✓

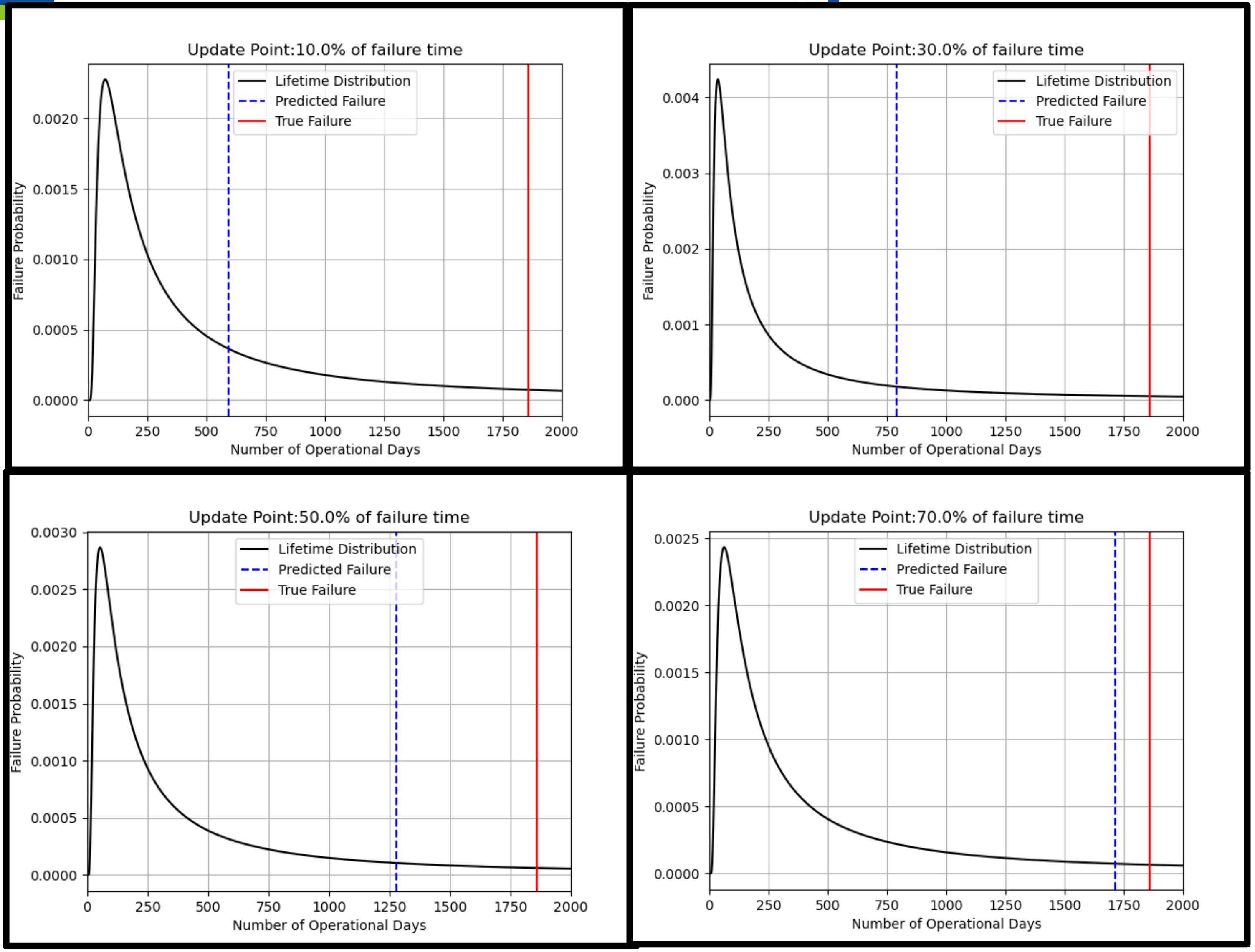
Reference 1: *NAGI Z. GEBRAEEL, MARK A. LAWLEY, RONG LI & JENNIFER K. RYAN (2005) Residual-life distributions from component degradation signals: A Bayesian approach, IIE Transactions, 37:6, 543-557, DOI: 10.1080/07408170590929018*

Reference 2: *ISO 20816-5:2018Mechanical vibration — Measurement and evaluation of machine vibration — Part 5: Machine sets in hydraulic power generating and pump-storage plants*

Data-driven Prognostics Framework



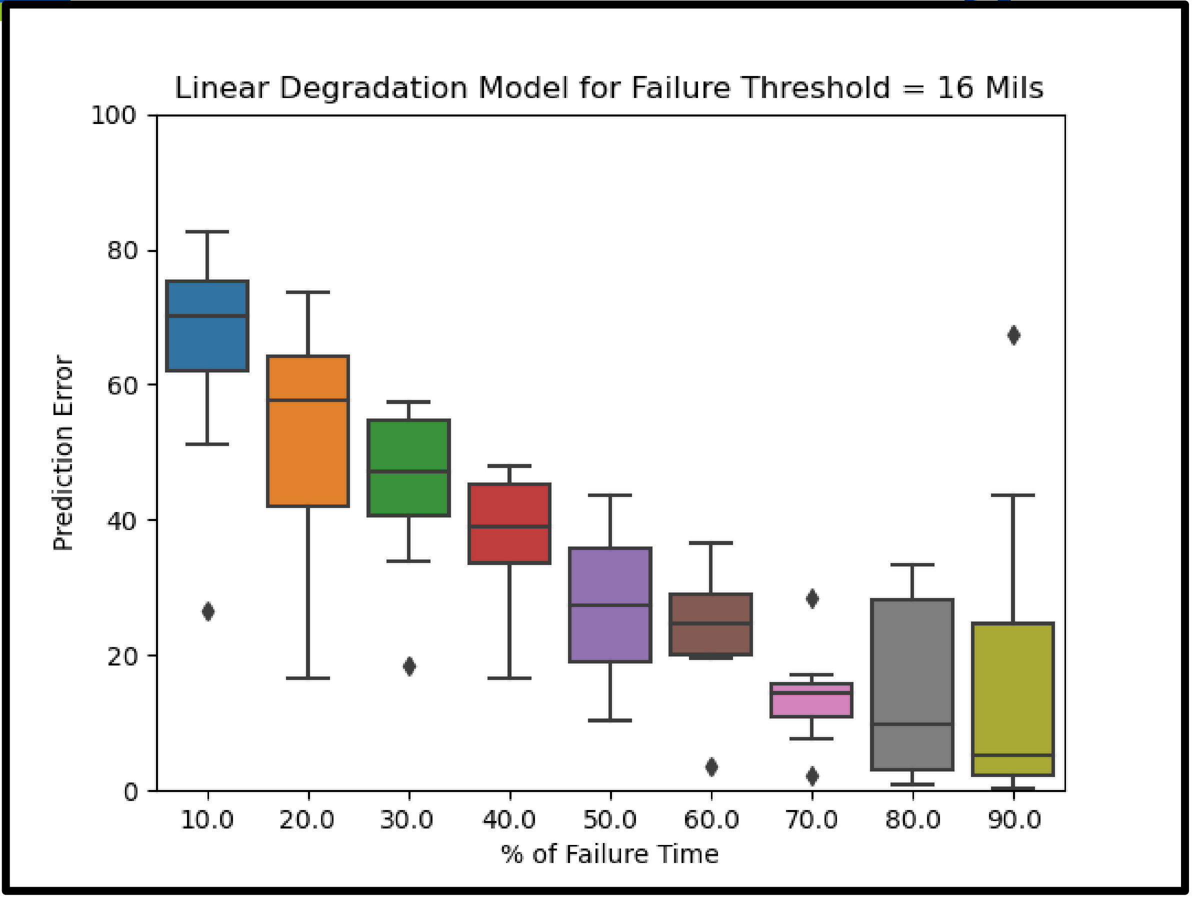
Predictive Modeling Results

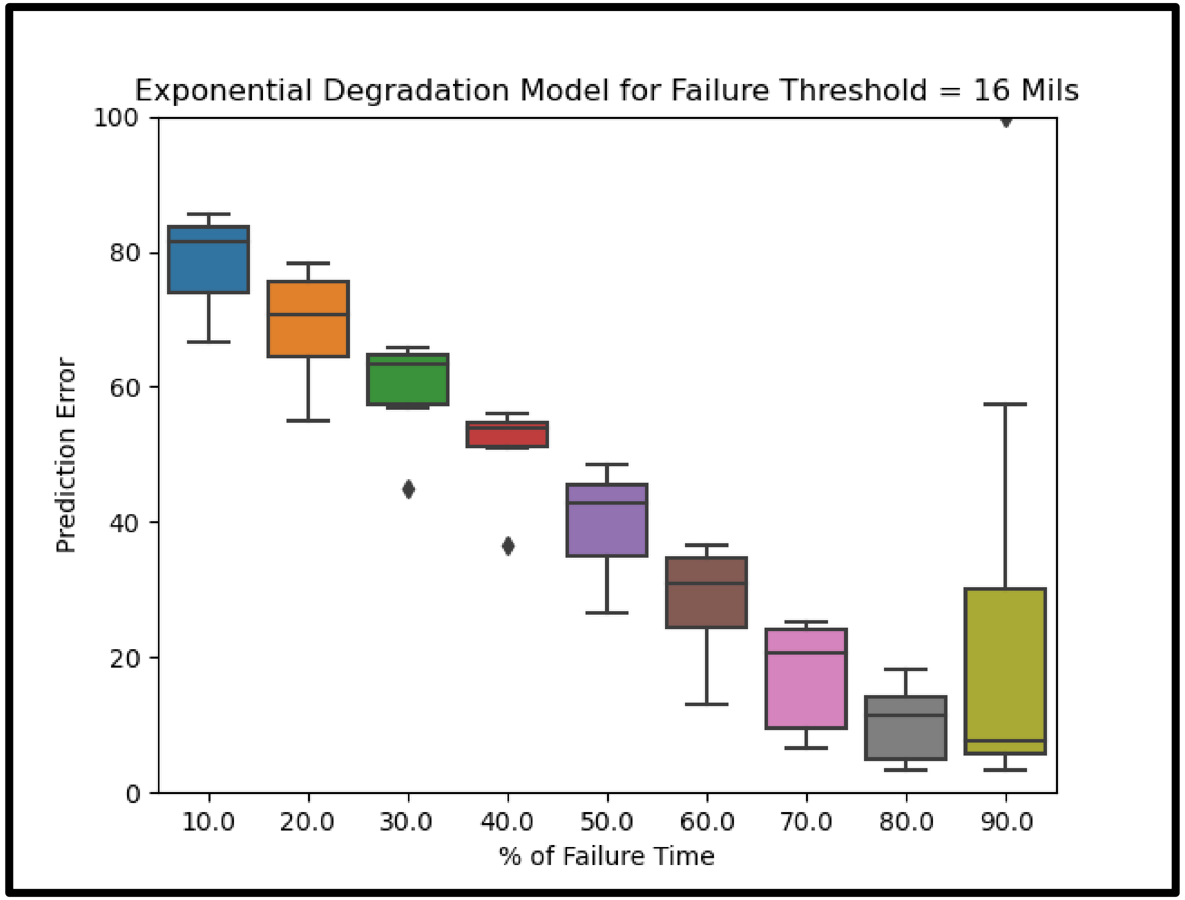


Lifetime distribution for sample bearing using linear model

Key Inference:
As observed data increase, the prediction accuracy increases

Predictive Modeling Results





Key Inference: Linear model *has better predictive performance* in terms of mean and uncertainty around predictions

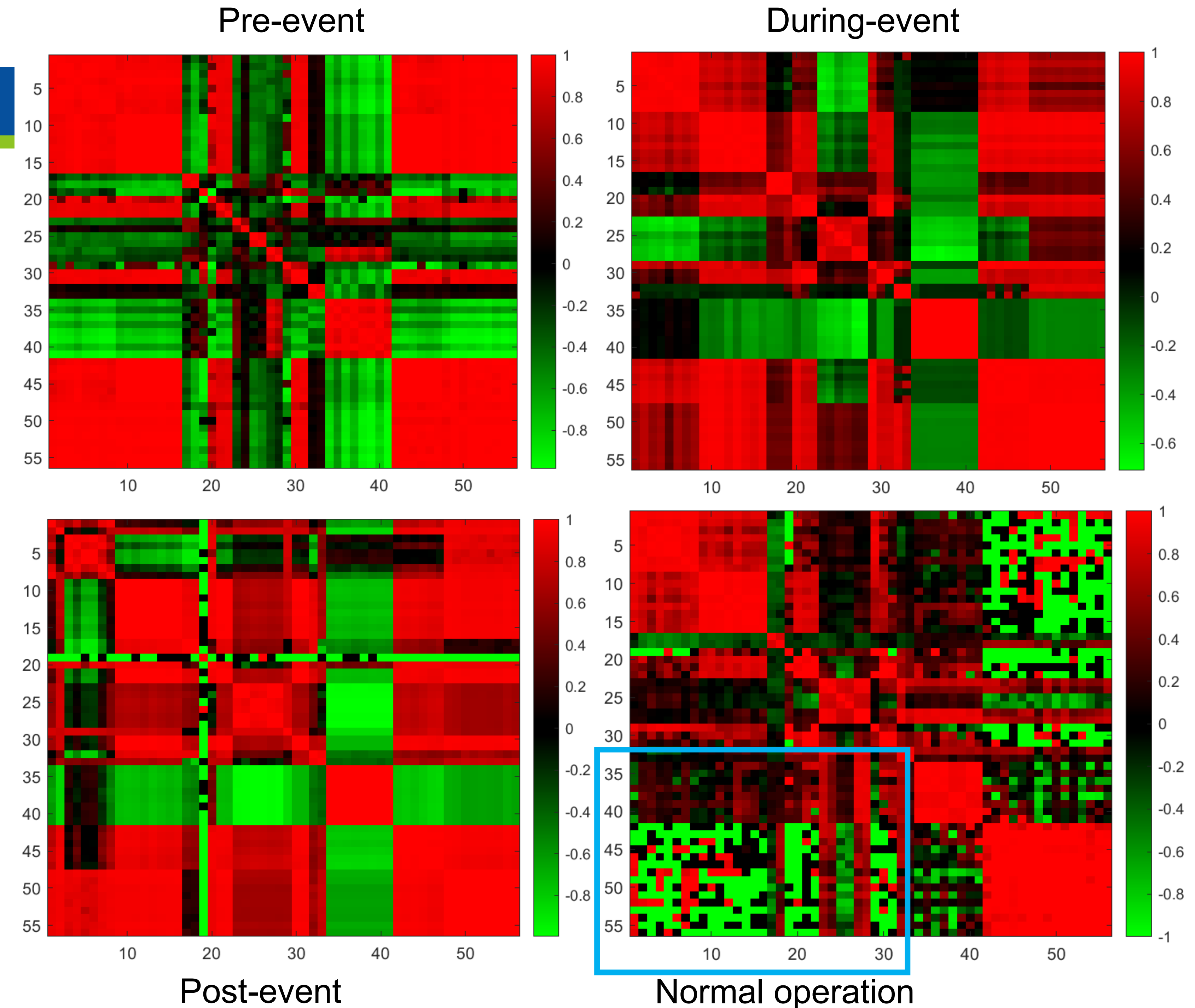
Two studies

I. Modeling hydropower degradation through vibration signal
II. Physic-informed degradation and prognostic

Physics-informed modeling

- Physics-informed model:
  Use of "***operating conditions***" in the degradation modeling
  - Computing power generation from rotor current & voltage data
  - Making data-driven prognostics model a function of site/powerhouse

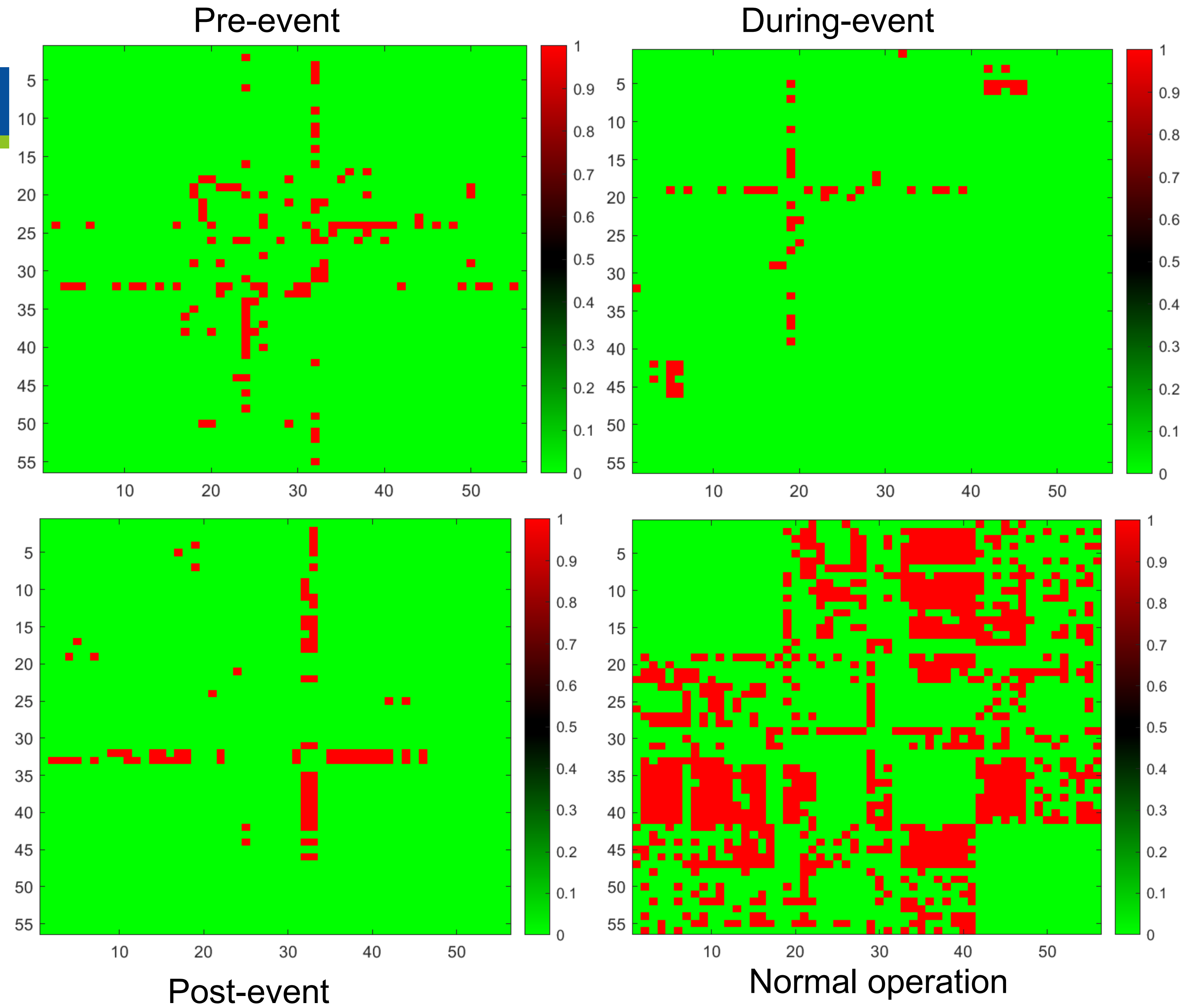
- Validating prognostics model with the events data
  - Predicted failure time should be closer to a bearing vibration event
    - If no maintenance: Verifying if the bearing continued to degrade vs nominal operations



Normal operation scenario has different correlation coefficient for stator and rotor measurements than the other scenarios.

1-19: Cooling system air temperature
20-22: Guide Bearing/Drive End Guide/Oil Cooler
23-28: Guide Bearing/Drive End Guide/shaft
29-31: Guide Bearing/Non-Drive End Guide/Oil Cooler
32-33: Rotor field current
34-41: Stator airgap vibration
42-47: Stator core temperature
48-56: Stator winding temperature measurements

Perform a t-test for correlation



- Green means statistically important
- Red means not statistically important
- Most of correlation coefficients are statistically significant during pre-/ during-/ post-event scenario
- A lot of correlation coefficients are not significant during normal operation

Physics-informed modeling

Standard bearing life formula in terms of incremental damage in the form of an ordinary differential equation [1]

$$\frac{da_{BRG}}{dt} = \frac{1}{c_1 c_2(t)} \left(\frac{P(t)}{C} \right)^{\frac{10}{3}}$$

$P(t)$ is dynamic bearing load (power generation from rotor current & voltage data)

$c_2(t) = g(\alpha_{GRS,t})$ — adjustment factor c_2 based on linear/exponential degradation $\alpha_{GRS,t}$

$\alpha_{GRS,t} = f(\alpha_{GRS,t-1}, x_t)$ — recurrent neural network for degradation

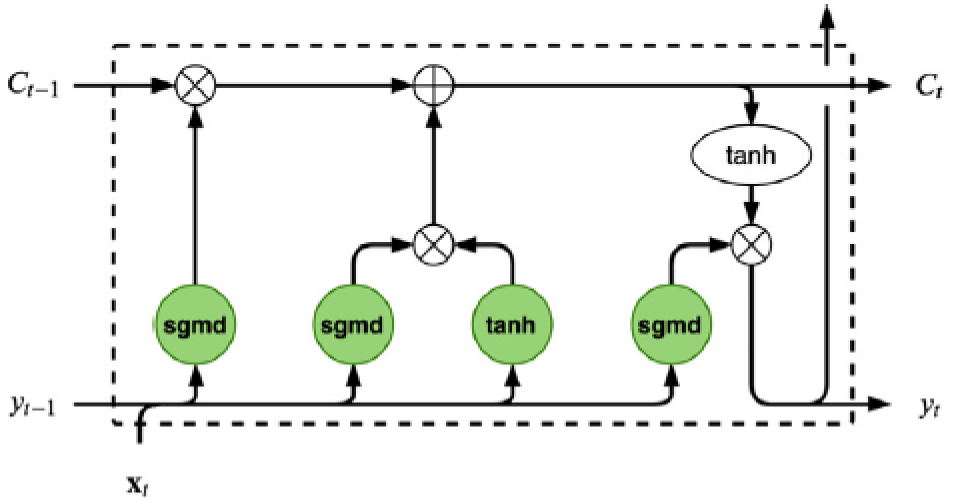
$c_1 = 1.0$ — reliability level factor

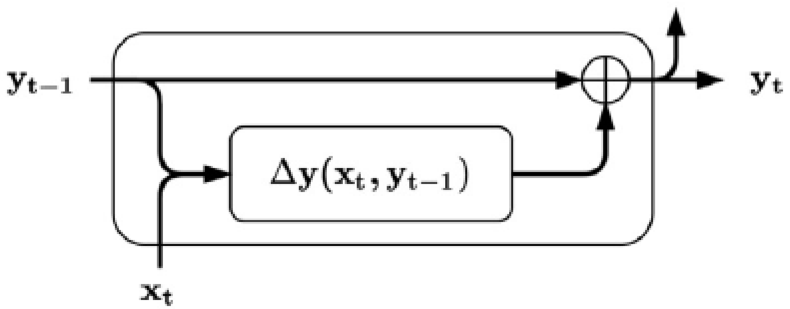
C — design load rating

[1] A hybrid physics-informed neural network for main bearing fatigue prognosis under grease quality variation

Physics-informed modeling

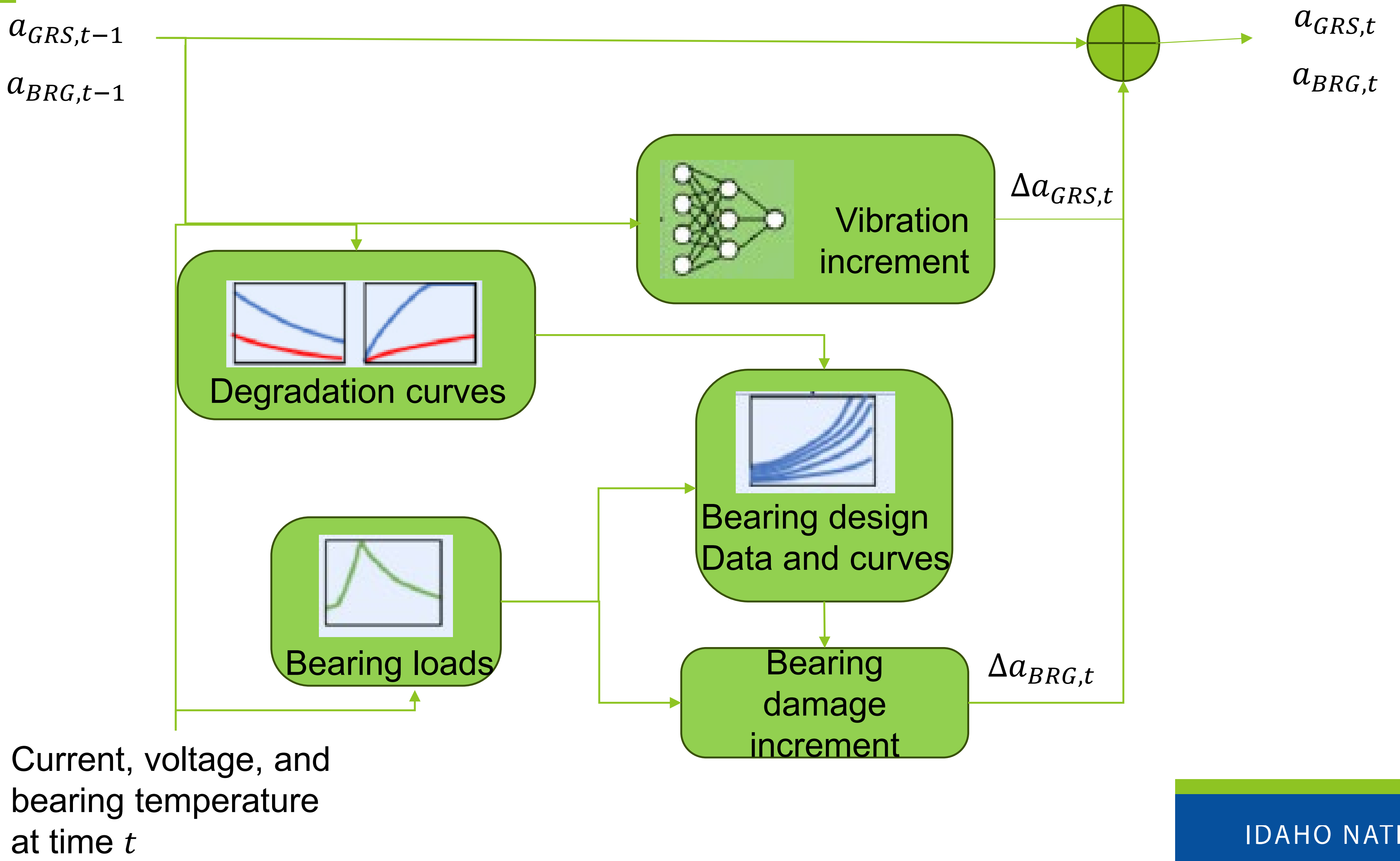
Expand the Euler integration cell to implement numerical integration of bearing life equation





$$a_t = f(x_t, a_{t-1})$$
$$a_t = [a_{BRG,t}, a_{GRS,t}]$$

Physics-informed Neural Network



Model training

The cumulative damage model training process with mapping to different quantiles

$$L_{50,GRS}(t) = f\left(T_{BRG}(t)\right)$$

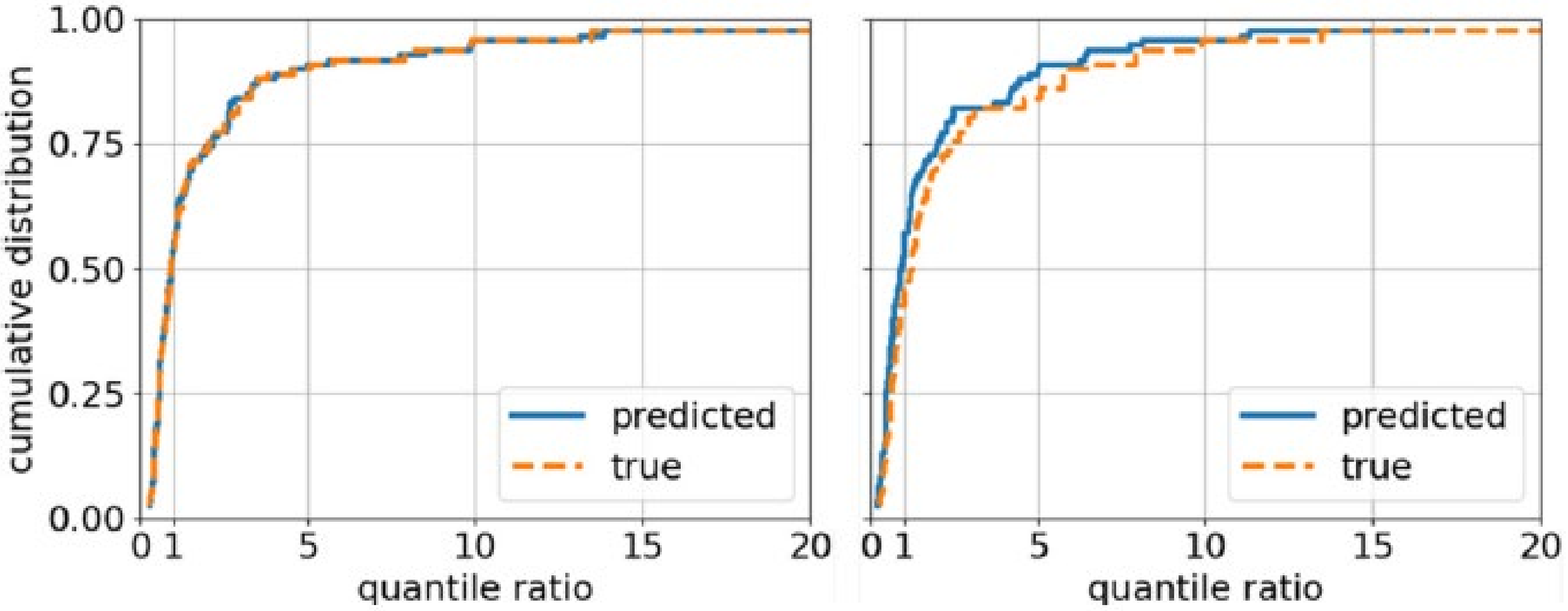
$$\Delta a_{50,GRS}(t) = \left(\frac{1}{L_{50,GRS}(t)}\right)^2$$

$$a_{50,GRS}(t) = \sum_{t=0}^{T} \Delta a_{50,GRS}(t)$$

$$a_{k,GRS}(T) = C_k \sum_{t=0}^{T} \left(\frac{1}{L_{50,GRS}(t)}\right)^2 = C_k a_{50,GRS}(T)$$ mapping the damage we want at a specific quantile

$$\min_{C_k} \frac{1}{N_o} \sum_{i=1}^{N_o} \left(a_{GRS_i} - C_k \times \hat{a}_{GRS_i}\right)^2, s.t. C_k > 0$$ Minimize quantile based loss function

Example Results



Empirical cumulative distribution of the quantile ratios predicted with models trained with different turbine

Questions

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Idaho National Laboratory

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