# Assessment of Fault Severity towards Prediction of the Remaining Useful Life


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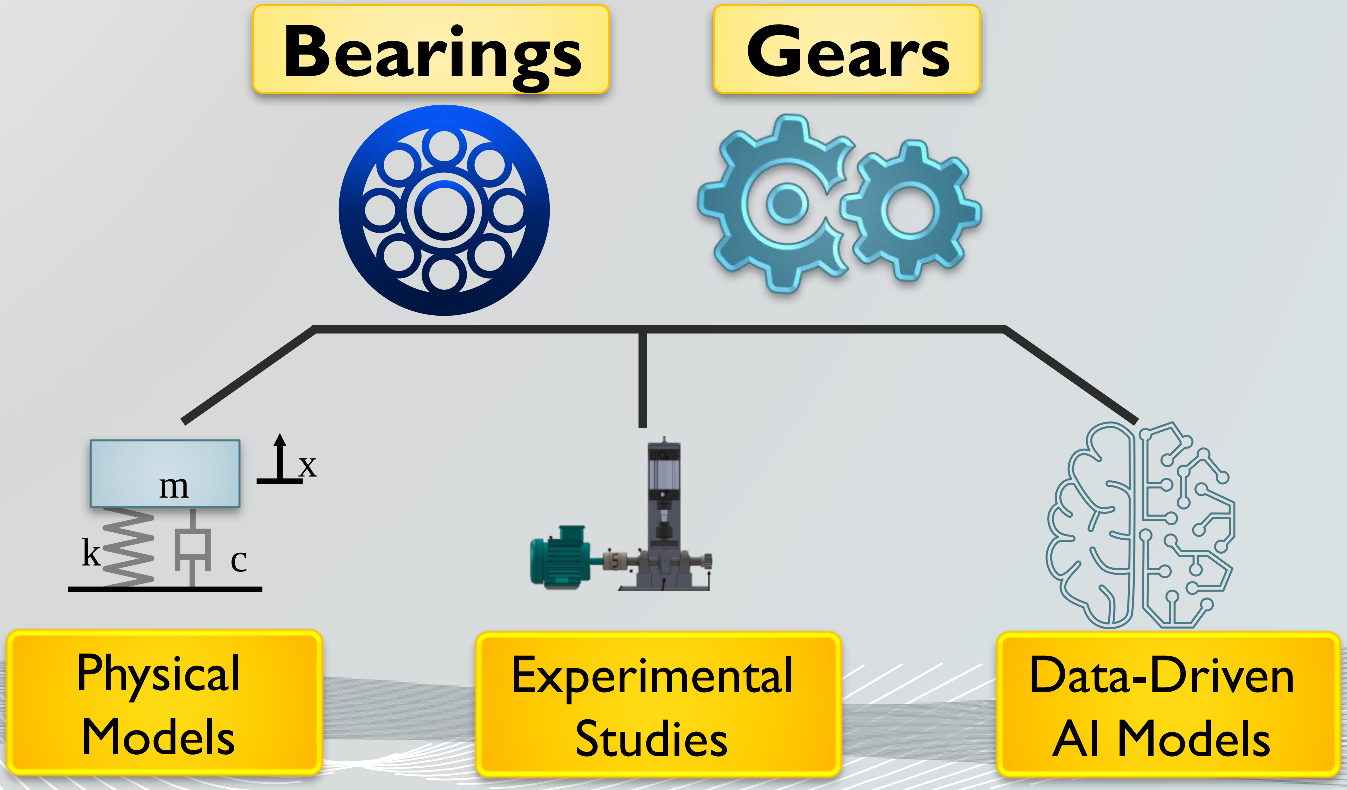
**Salt Lake City, Utah**
**October 28 - November 2, 2023**

# BGU PHM Lab

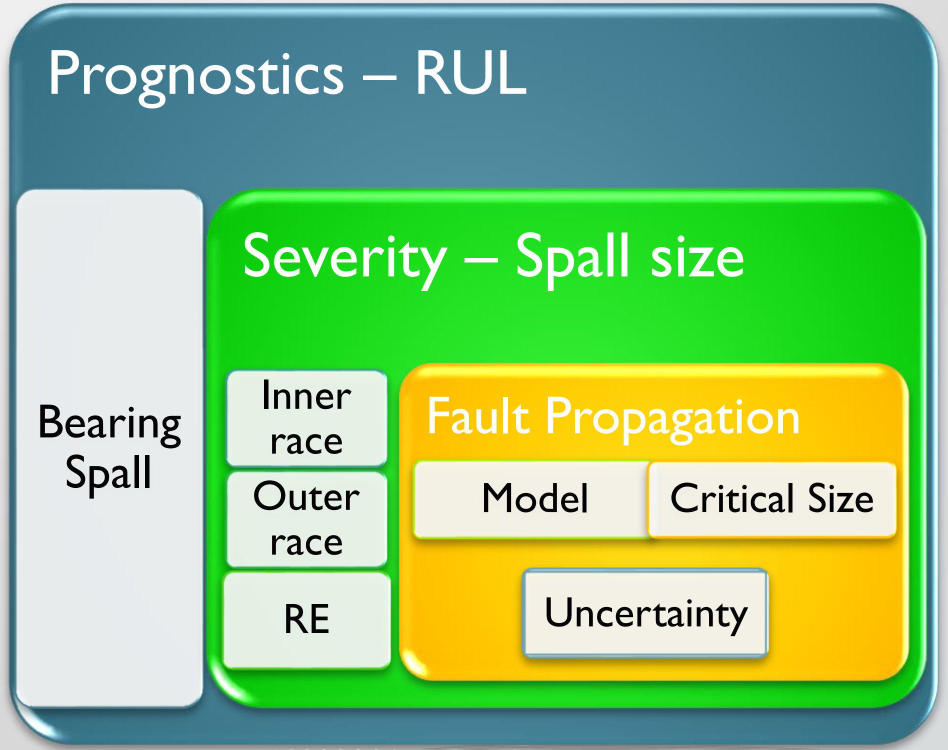
- ✓ Creating an **Israeli excellence center** for advanced health monitoring of machinery.
- ✓ **Cooperation** with partners from the academia, industry, development centers, and defense forces.

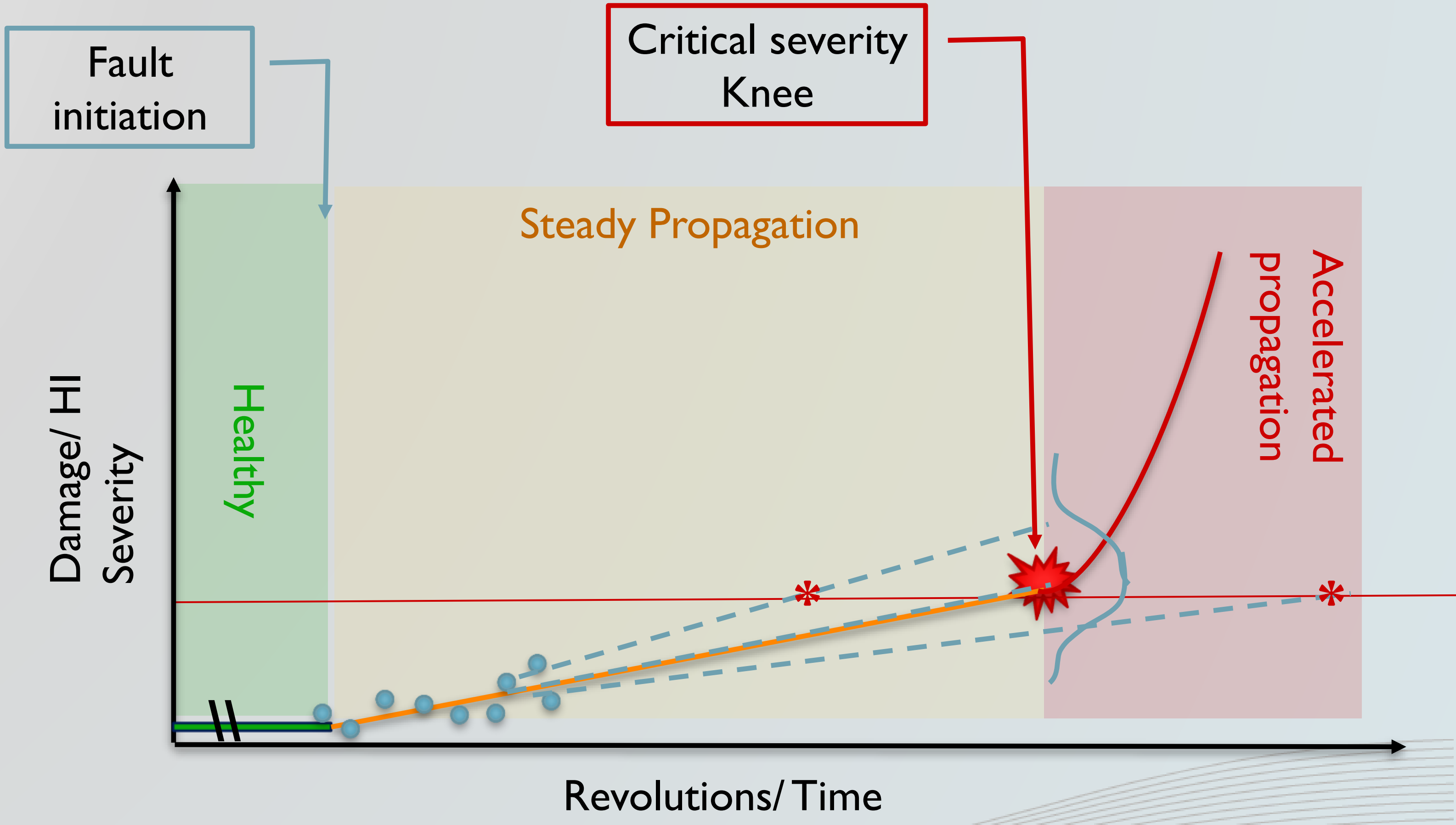


# Agenda

- Types of models
- Hybrid systems
  - Example of fusion of  physical knowledge with deep learning
  - Example of domain adaptation for zero shot learning from simulation to real data
- Advanced PHM Research for Engine Mechanical Components (collaboration with AFRL)
  - Research methodology
  - Physical models contribution to severity estimation based on ODM and vibrations
- Endurance Tests of Roller Bearings (collaboration with SKF)
  - New CIs for severity estimation

# RUL PROGNOSTICS



# MODELS

Sensor location

Operation conditions

Machine health status

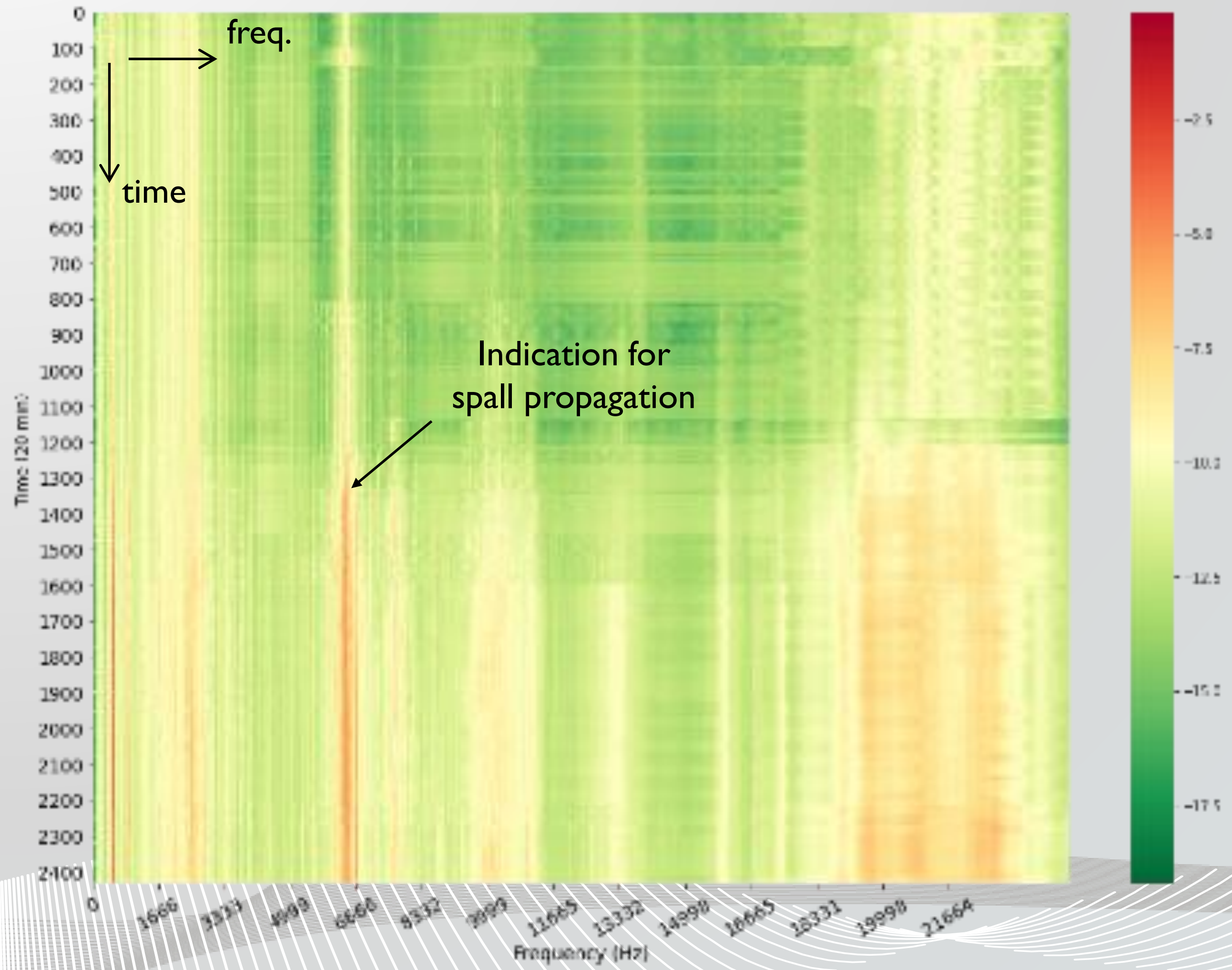
| Model | Types | ✔ | ✘ |
|---|---|---|---|
| Physical | • Dynamic<br>• Kinematic – Signal<br>• Finite Elements | • **Interpretable**<br>• Generalization<br>• Simulate operation conditions & sensors | • Limited by assumptions<br>• **Domain expertise**<br>• **Complex** |
| Data driven | • Statistical<br>• ML – Un/Supervised<br>• Deep Learning | • **Large feature space**<br>• **No need for expert**<br>• Automatic feature extraction/ selection | • **Black box**<br>• **Complete, labeled and immense set of examples** |
| Hybrid | • Physics based preprocessing<br>• CI extraction<br>• HIs or classification | • Learn parameters to fit data<br>• Use insights from data analysis to develop models<br>• Use physical knowledge to guide the learning process<br>• Fuse estimates from two different approaches | |

# EXAMPLE
# USING PHYSICAL KNOWLEDGE TO GUIDE THE LEARNING PROCESS

Deep Learning Models

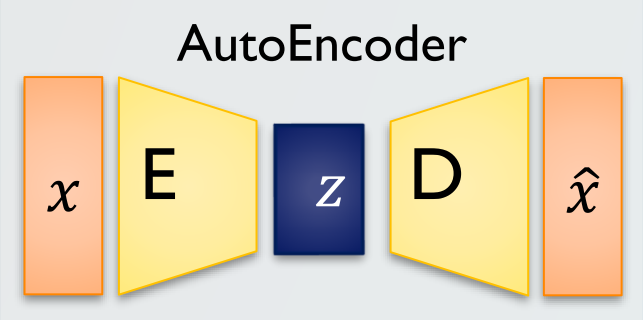
# HYBRID MODEL FOR BEARINGS

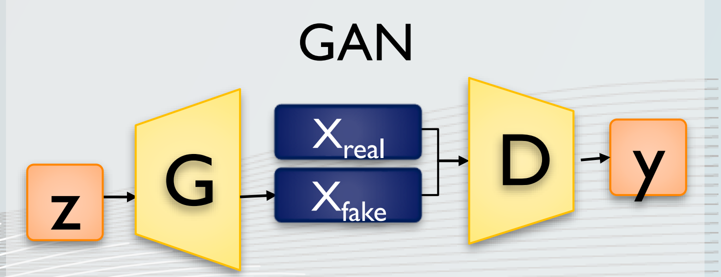
## *Bearing Endurance Test*





## *Deep Learning AI Models*



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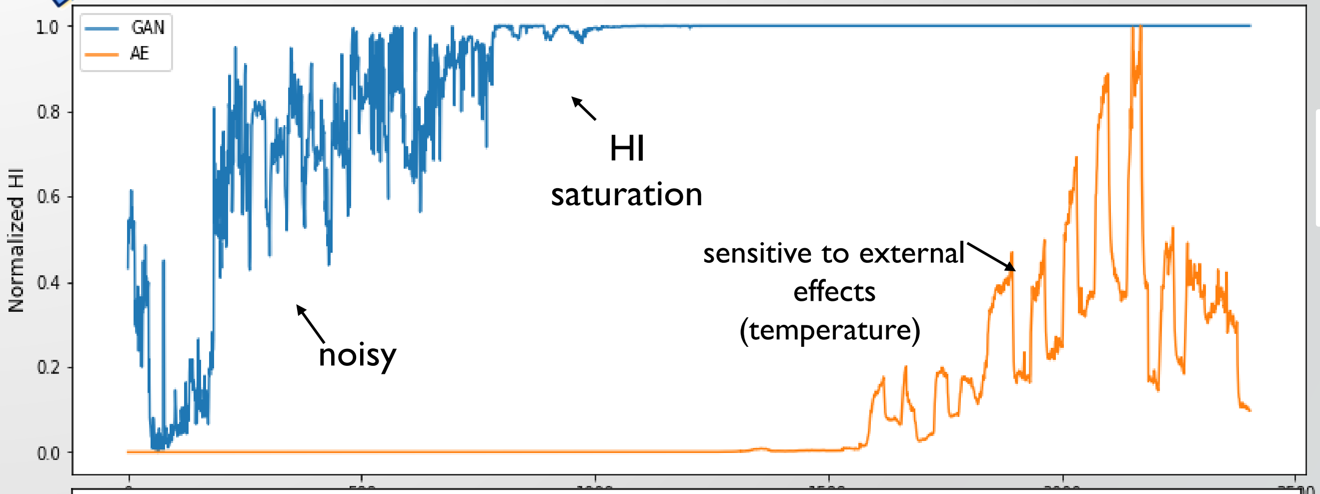
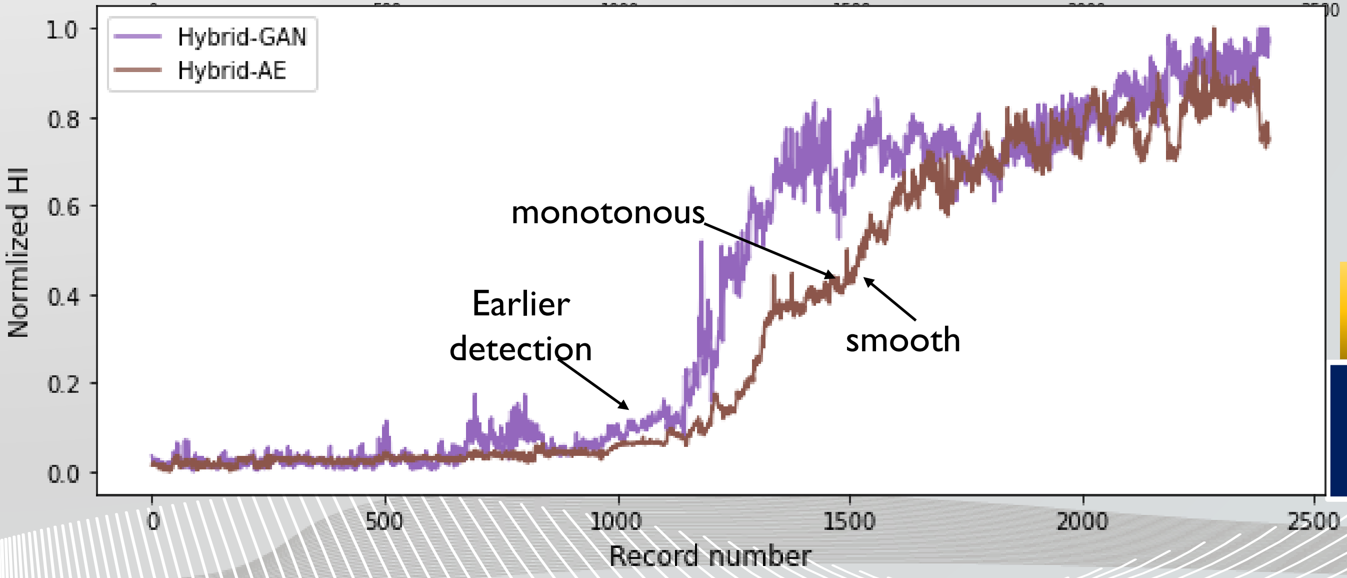
# HYBRID MODEL FOR BEARINGS

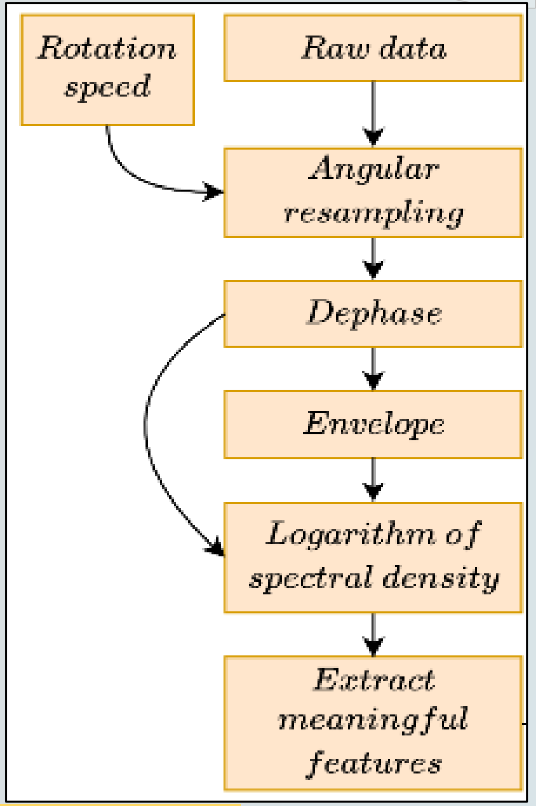



## AI-based approach

Raw Data → AI Model → HI Trend

Bearing analysis




## Hybrid physical-AI approach

Raw Data → Physical Processing → AI Model → HI Trend

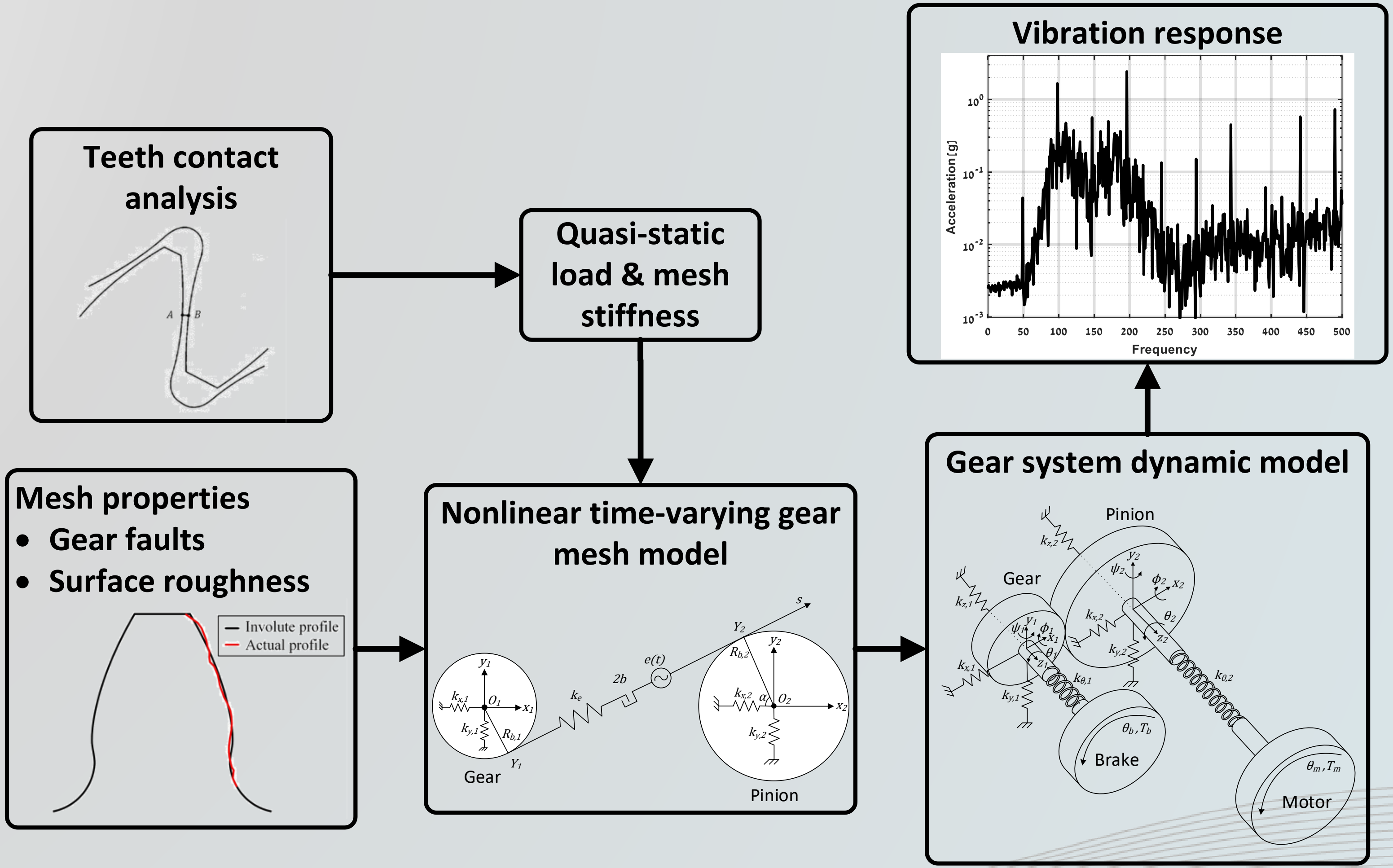
# Hybrid System Conclusions

- The deep learning algorithms cannot separate between different sources of vibration excitation (gears, unbalance shafts, temperature, contaminated grease or oil, etc.)
- The application of signal processing for separation of excitations is crucial
- An additional process of separation can be done in the feature extraction stage. The most effective separation is based on physical reasoning.

# DATA AUGMENTATION AND DOMAIN ADAPTATION

# GEAR DYNAMIC MODEL

- Spall like faults
- Cracks
- Missing tooth
- Chipped tooth
- Backlash
- Unbalance, Misalignment & Eccentricity
- Surface roughness



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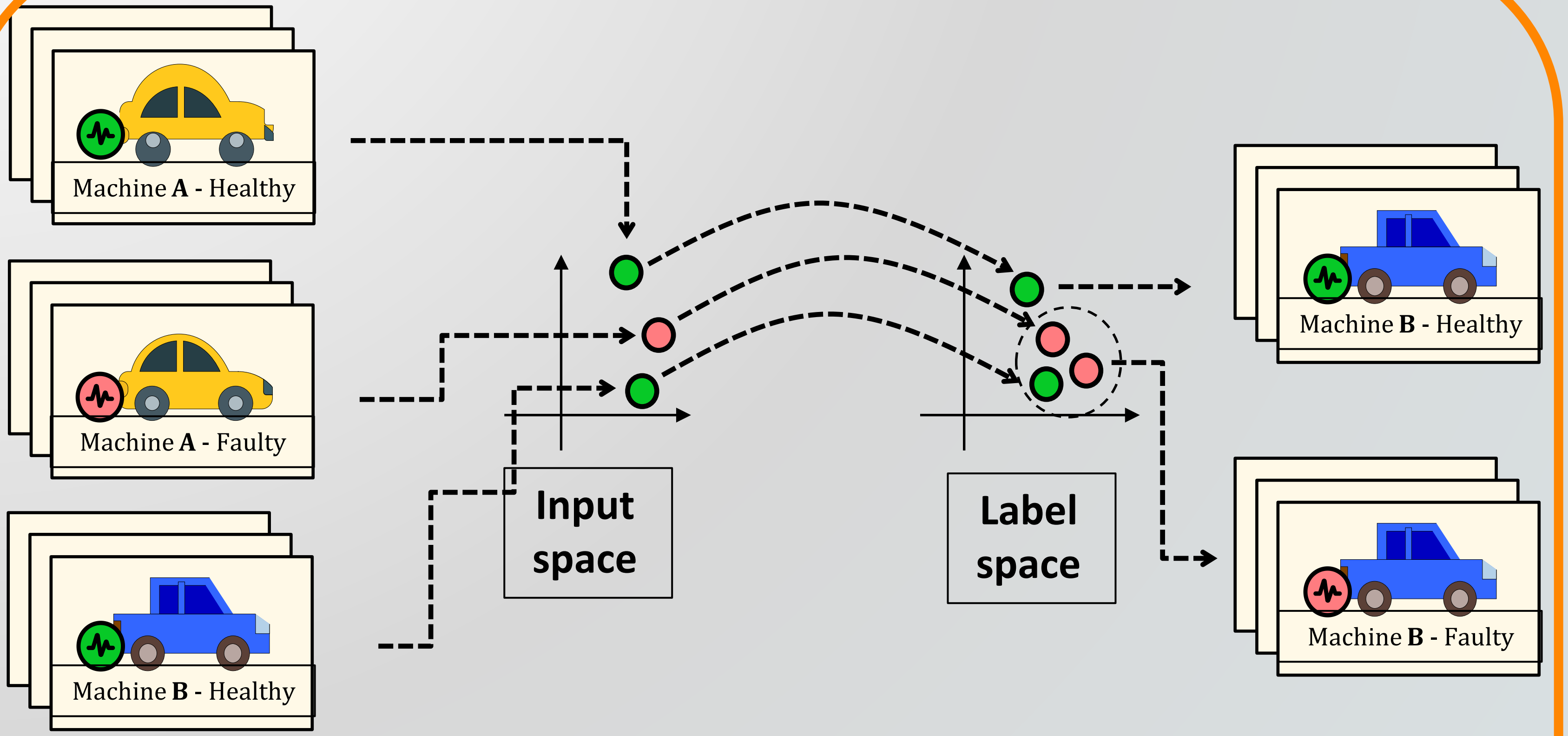
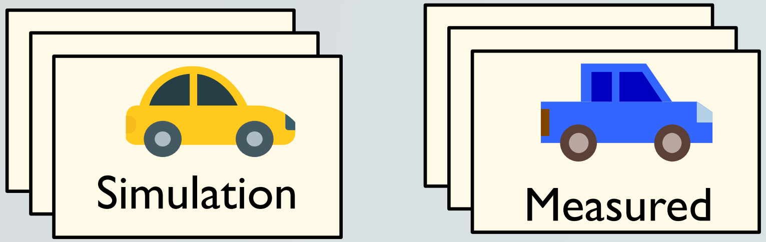
# ZERO-SHOT LEARNING
# FROM SIMULATION TO REAL DATA

**Predicting classes in the test set for which no examples exist in the training set**




**NO faulty samples of B**

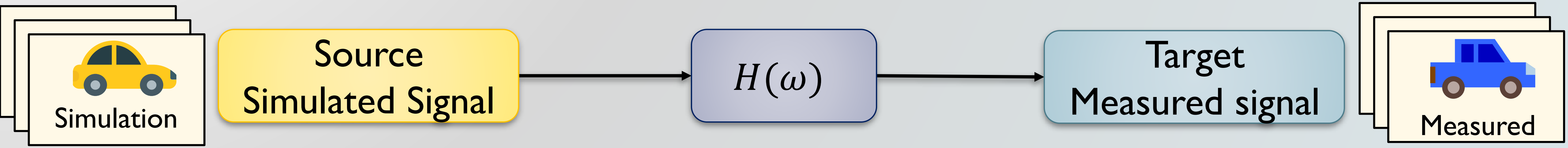



- The dynamic model can generate a large amount of healthy and faulty data with different severities
- Only healthy measurements are available on the real system

# DOMAIN ADAPTATION

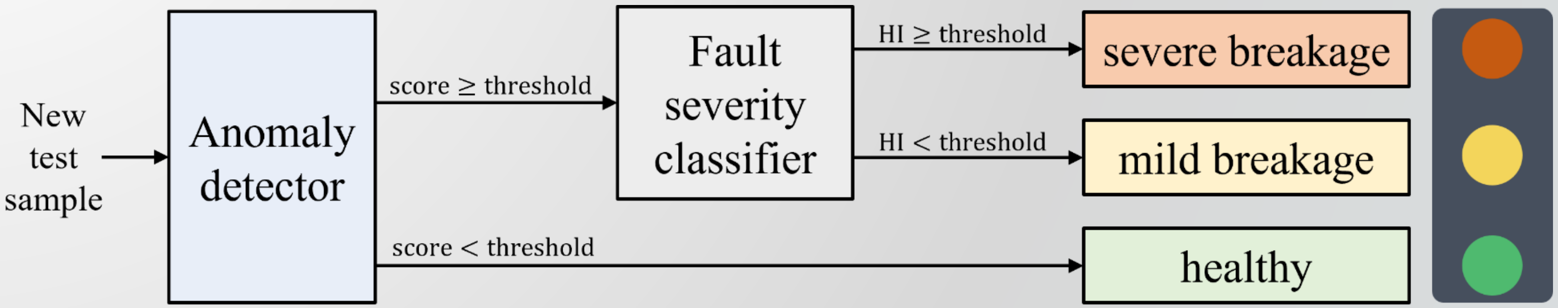
## Transfer learning

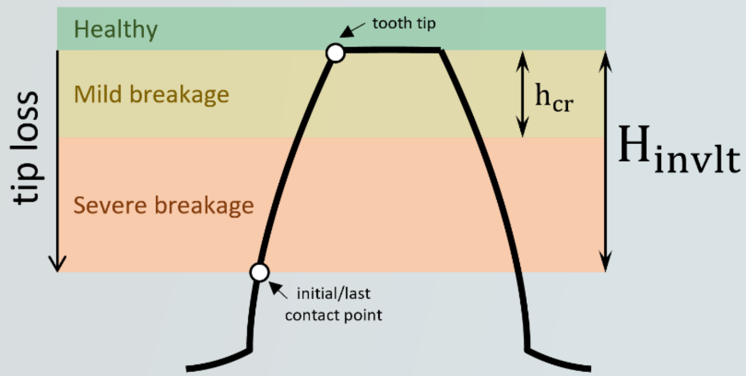
- The transfer function $\mathrm{H}(\omega)$ is estimated based **only on measured healthy signals**
- Passing simulated signal through estimated transfer function generates faulty examples of measured signals → used for training




- Adapting knowledge/ data from one source to another
  - Improving generalization
  - Effective when target domain data is unavailable, but source domain data is available

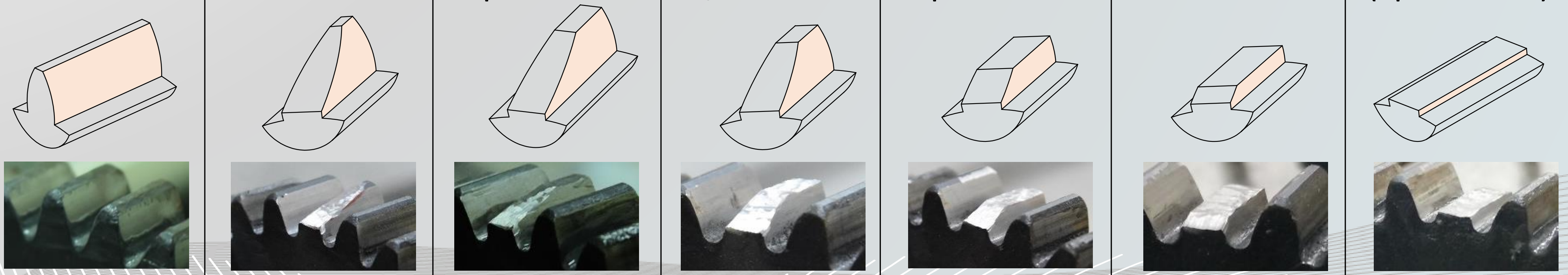
# STRATEGY FOR SEVERITY ESTIMATION

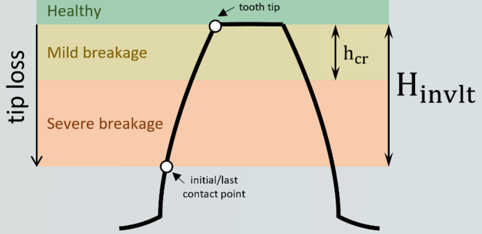



**Estimating tooth breakage fault severity as a combined anomaly detection + binary classification problem**

| Healthy | Chipping (Tip loss of 0 mm) | Chipping + Tip loss of 1 mm | Chipping + Tip loss of 2 mm | Chipping + Tip loss of 3 mm | Chipping + Tip loss of 4 mm | Missing tooth (Tip loss of 5 mm) |
|---|---|---|---|---|---|---|
| y = | y = | y = | y = | y = | y = | y = |

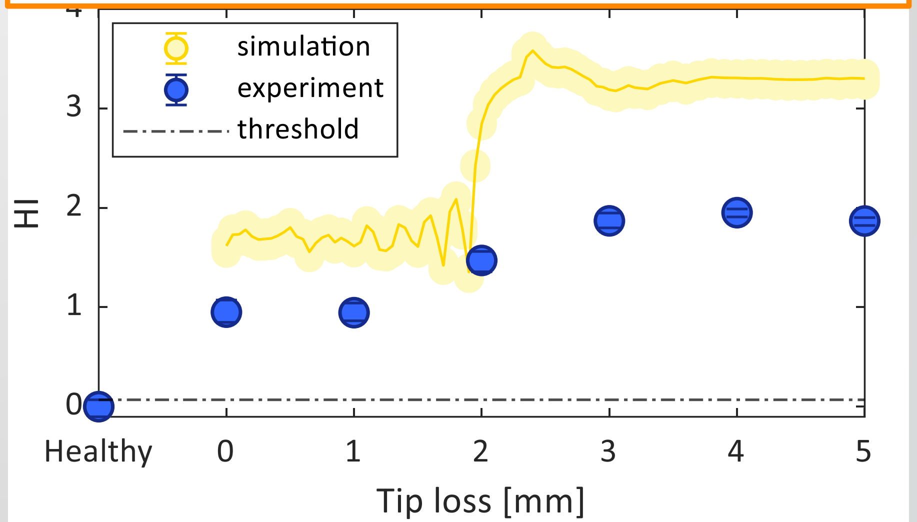





# RESULTS

Physical features → Standardization → PCA → Standardization → RMS → Log → **HI**

## Sensitive HI (72 features)

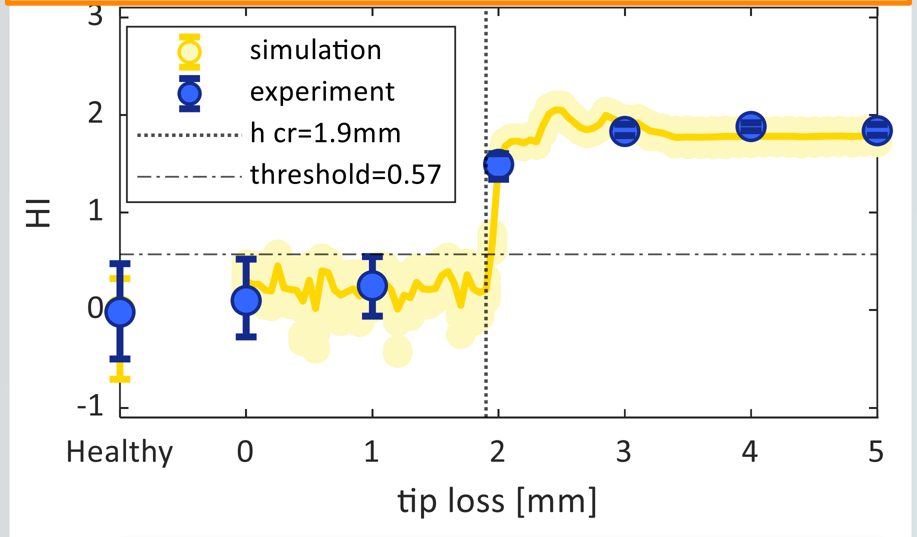



**Anomaly Detector**

(separates ● from ● ● )

Training sets of healthy measured and simulated data for iForest, kNN, OCSVM, HI

## Basic HI (4 features)




**Severity Classifier**

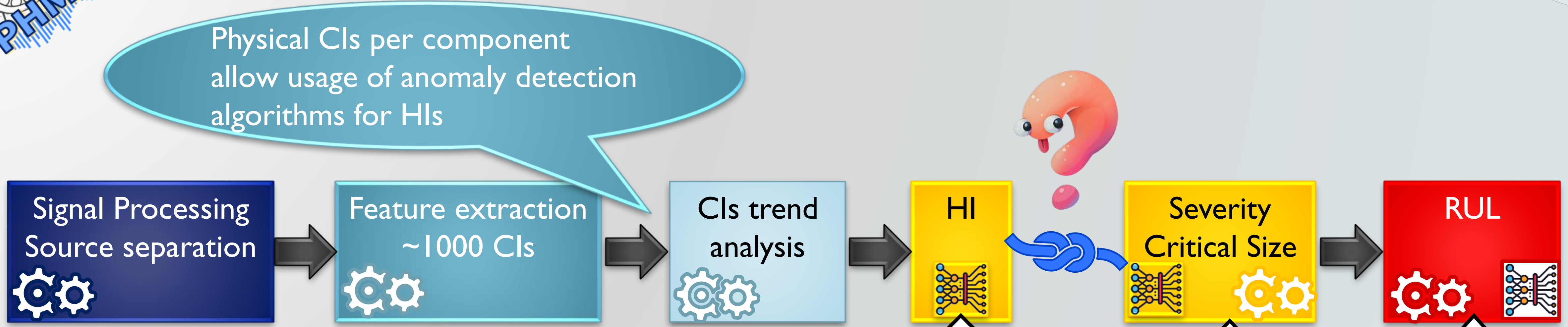
(separates ● from ● ● )

Joint training set of healthy measured data and healthy & faulty simulations

# Zero Shot Learning and Data Augmentation

- The feasibility of zero shot learning with data augmented based on simulation was proven
- It was demonstrated how a rich data set of healthy cases containing a large feature space can be used with anomaly detectors
- The threshold for the fault severity classifier is determined based on physical understanding
- Feature engineering can be enhanced by relying on physical methods (e.g. transfer function)

# HYBRID ARCHITECTURE




- ❑ Data augmentation – generate artificial signals
  - ▪ Physical TDM hybrid simulation
    - ✓ Suppress the effects of speed fluctuations
    - ✓ Interference of other rotating components
  - ▪ Learn transfer function effects
- ❑ Domain adaptation
  - ▪ TDM – transfer across different machines
  - ▪ TIM – transfer in the identical machine (operation conditions, tolerances…)

Training Data ?
- ✓ Simulations
- ✓ Real
- ✓ Lab tests

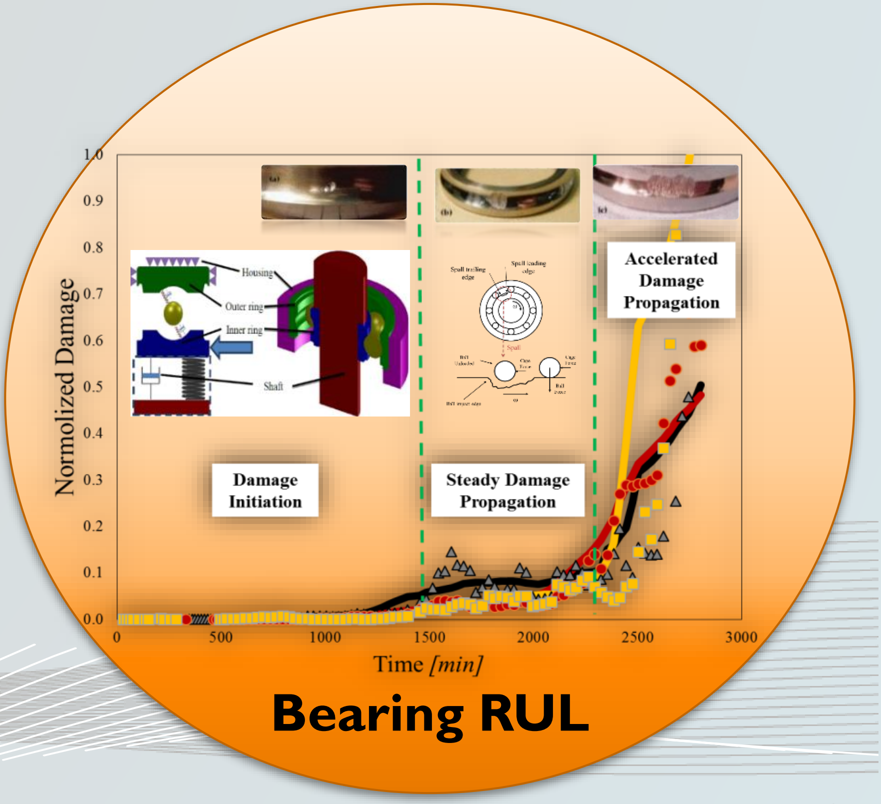
**Feature engineering**

Physical

AI

# PHYSICAL MODELS & SEVERITY ESTIMATION

Bearings



# Theoretical Background

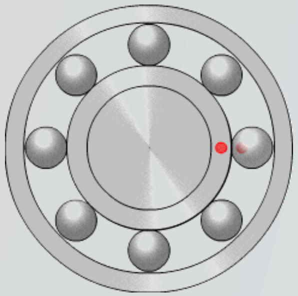
## Bearing tones

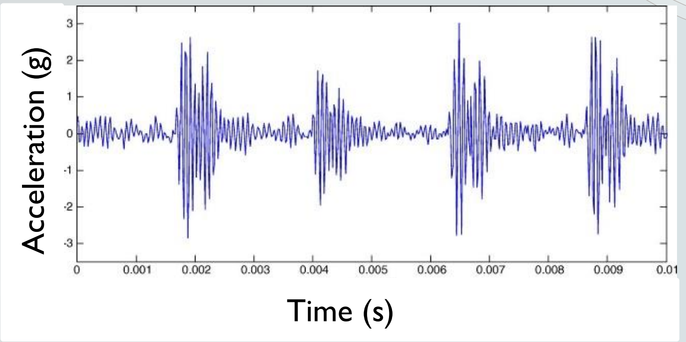
$$BPFO = \frac{f_r}{2} \cdot n \cdot \left[1 - \left(\frac{B_D}{P_D}\right) \cdot \cos(\phi)\right]$$

$$BPFI = \frac{f_r}{2} \cdot n \cdot \left[1 + \left(\frac{B_D}{P_D}\right) \cdot \cos(\phi)\right]$$

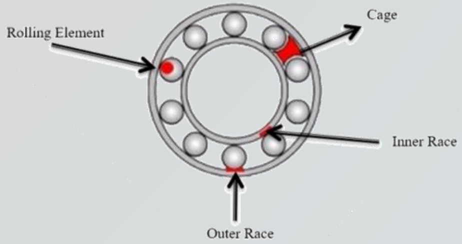
$$FTF = \frac{f_r}{2} \cdot \left[1 - \left(\frac{B_D}{P_D}\right) \cdot \cos(\phi)\right]$$

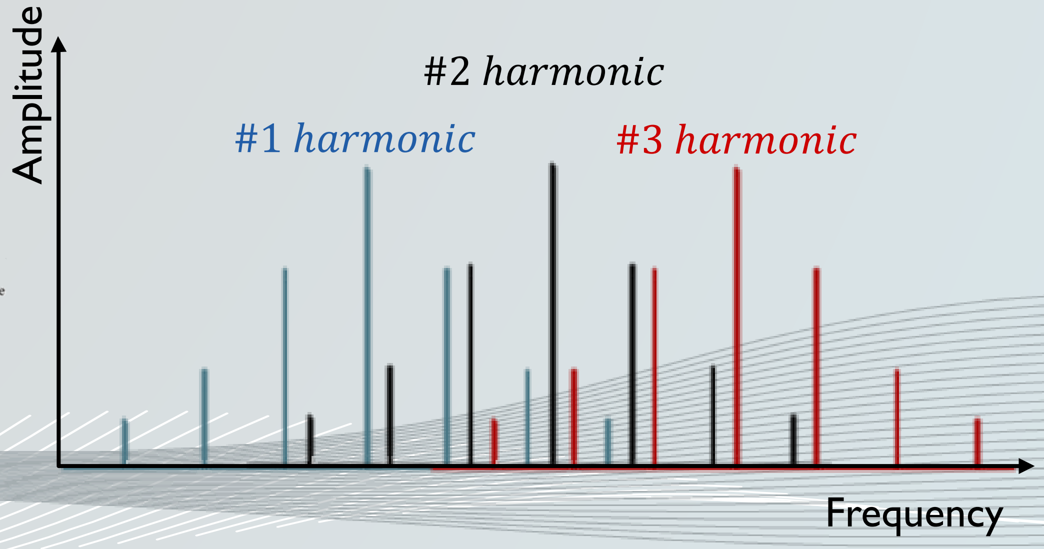
$$BSF = \frac{1}{2} \cdot \frac{P_D}{B_D} \cdot \left[1 - \left(\frac{B_D}{P_D}\right)^2 \cdot \cos(\phi)^2\right]$$






- Amplitude modulation (SB)
- High Harmonics

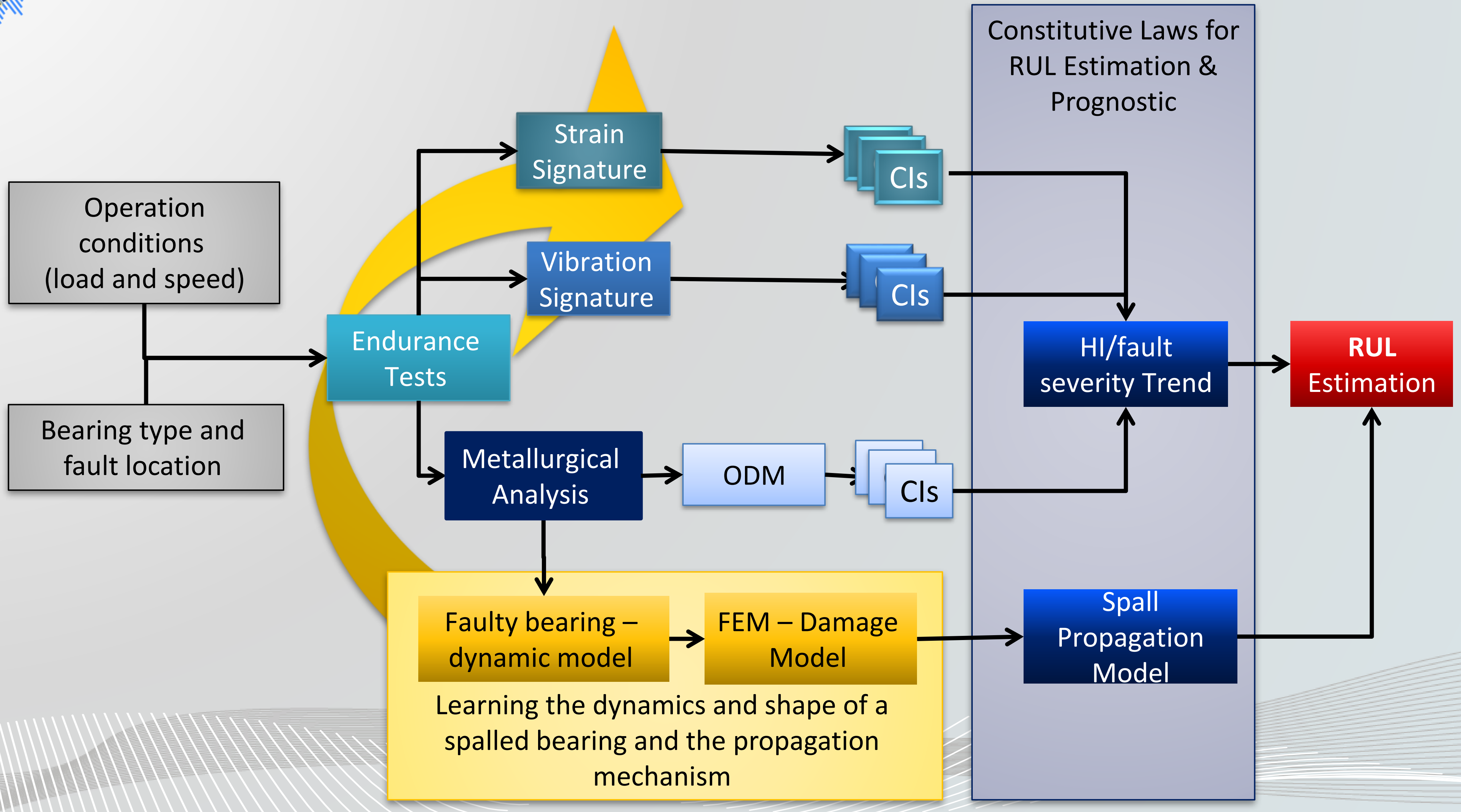



# ADVANCED PHM RESEARCH FOR ENGINE MECHANICAL COMPONENTS

Endurance Tests of Angular Contact Bearings

# RESEARCH METHODOLOGY



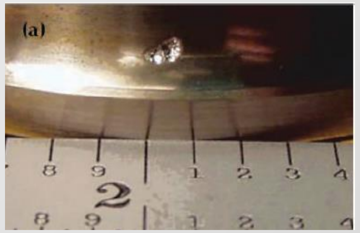
# EXPERIMENTAL TEST PROCEDURE

$Load: 10000N \rightarrow 5500N$
$Rotating\ speed: 10000RPM$

Endurance Tests → Fault Indentation → Spall Initiation → Spall Propagation

Spall Initiation → NDT Metallurgical Analysis

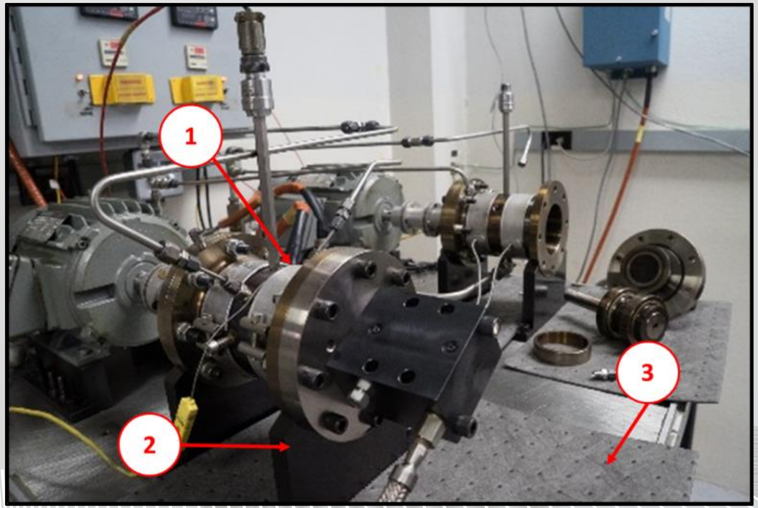
Spall Propagation → Destructive Metallurgical Analysis





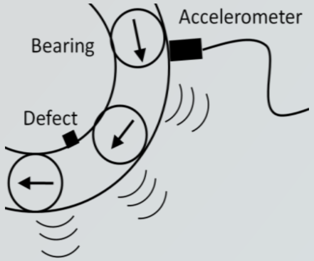
NDT Metallurgical Analysis


Destructive Metallurgical Analysis


ODM – Mass loss

Vibrations

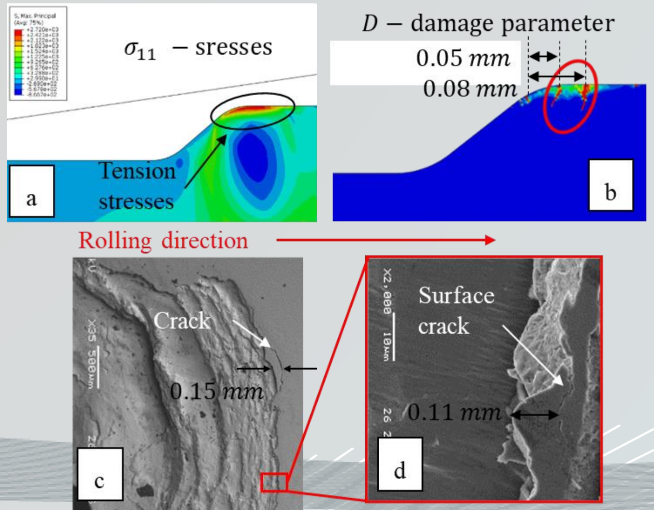



8 52100 bearings
6 M50 hybrid bearings
2 tri-axial vibration sensors – locations 1 and 3
RPM sensor

Sampling rate 50kHz 1min every 3 min
ODM data every 5 sec

# Insights from the Metallurgical Analysis

- Spall depth depends on the load and can be calculated by Hertz contact theory
- Spall growth stages:
  - Growth to race width
  - Growth both upstream and downstream, mainly in rolling direction (upstream)

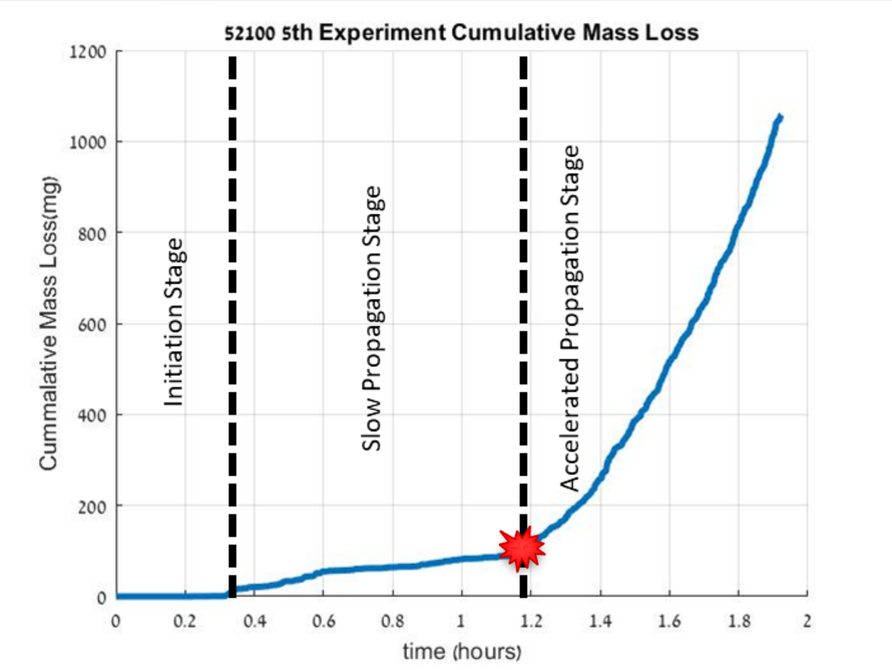


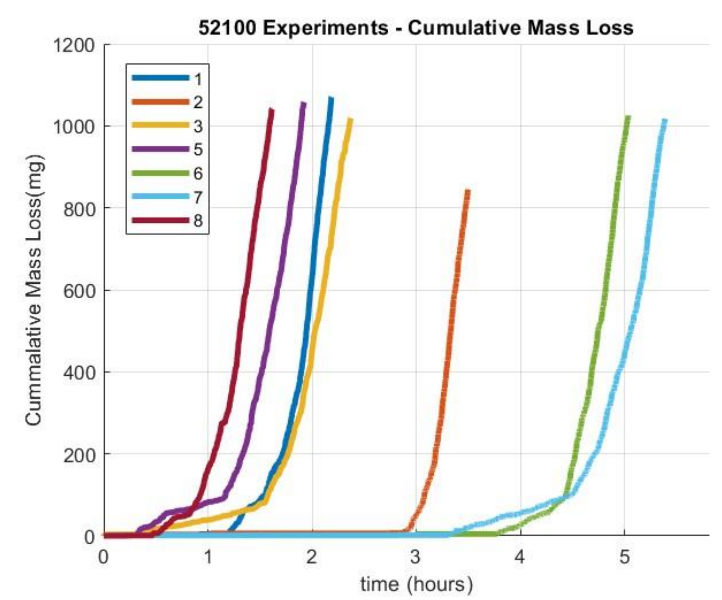
# OIL DEBRIS MONITORING (ODM)

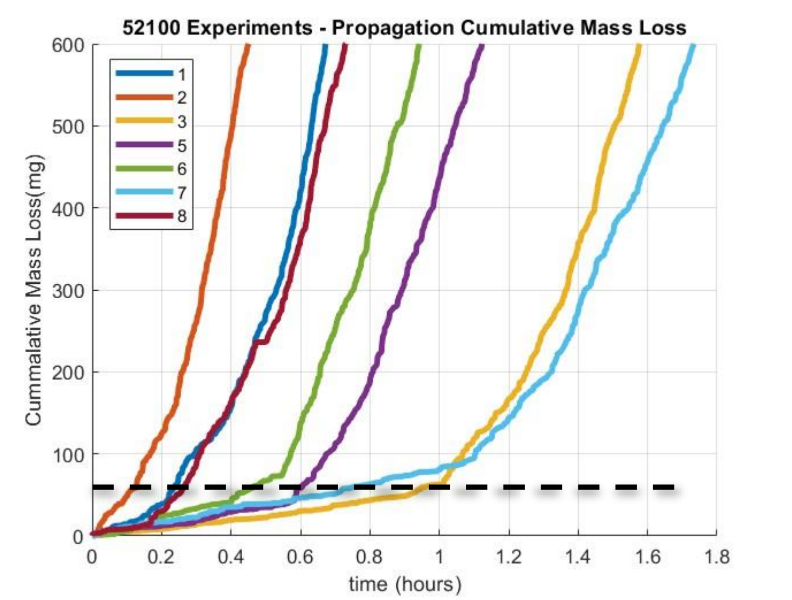
- Integrated AFRL ODM Sensor measures the amount and size of particles in the oil line
- Provides
  - Count of particles in 13 pre-defined size bins
  - Estimated total mass loss

# PARTICLE MASS LOSS

- Initiation time  difference
- “Knee” Point
- Transition to Accelerated Propagation stage
- Relatively similar in the propagation stage



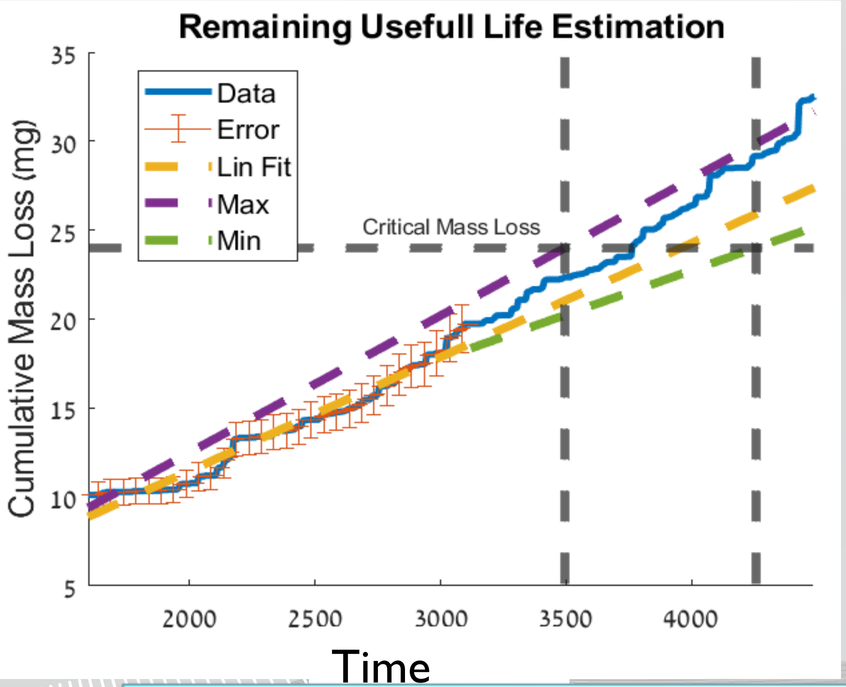



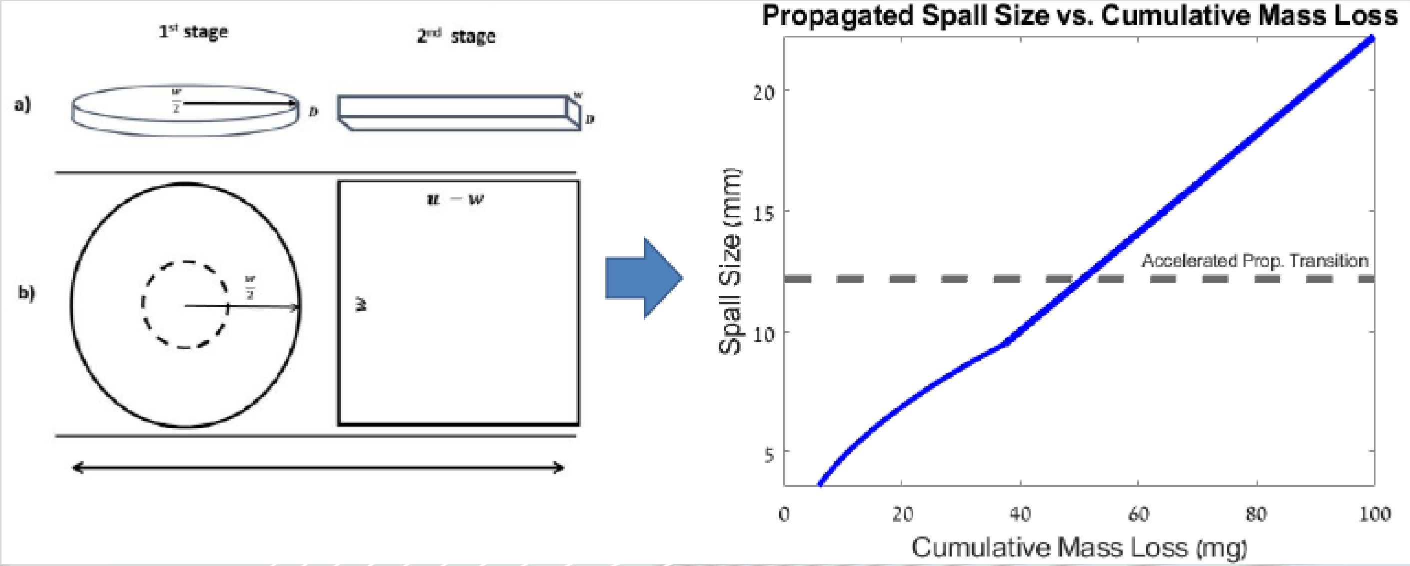
# ODM MODEL

severity

$$V = \frac{\rho}{M}$$

- Small → Large spall size
- Flat cylinder with growing diameter → flat cylinder + rectangular cuboid




Enable Physics-based Prognostics of Remaining Useful Life (RUL) based on ODM

# DYNAMIC MODEL

# BEARING DYNAMIC MODEL

- Validated and published
- Simulate the vibration signatures of the bearing with spalls of various sizes and locations
- Allows the interpretation of the bearing dynamic behavior and the effects on the vibration signatures

**Inputs**

Fault Size & Geometry

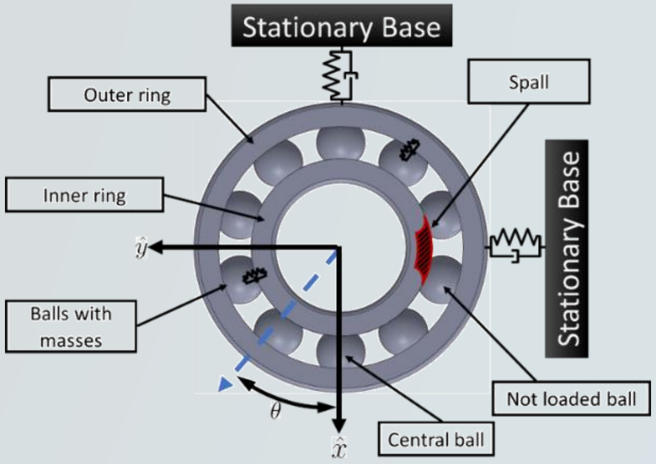
Bearing type
- Deep Grove
- Angular Contact

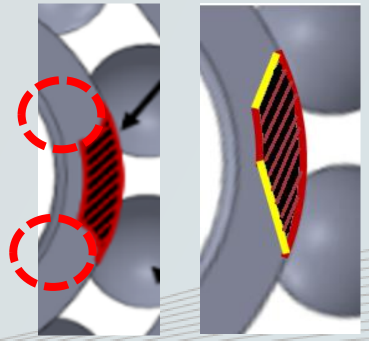
Fault Location
- Outer Race
- Inner Race

Operating Conditions
- Rotating Speed
- Load

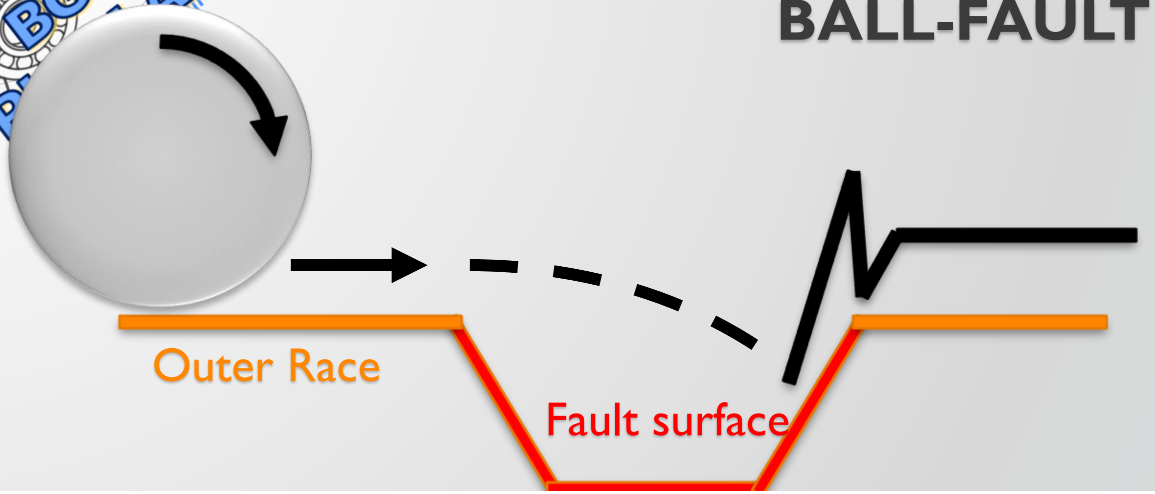
**Outputs**

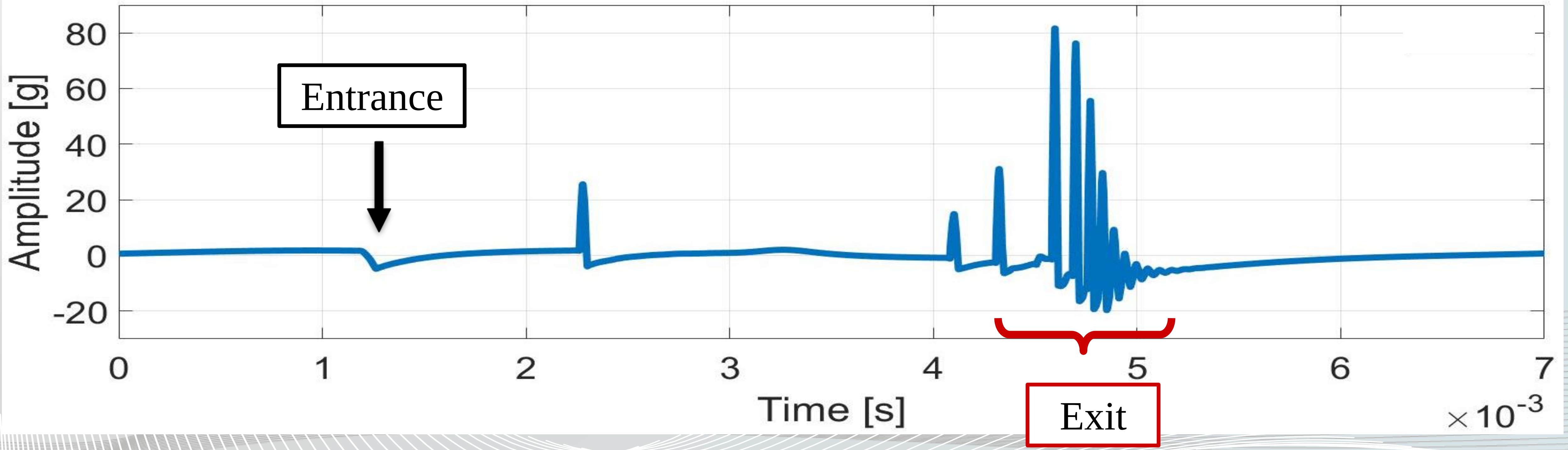
- Locations
- Velocity
- Acceleration
- Normal Force
- Friction



# BALL-FAULT INTERACTION



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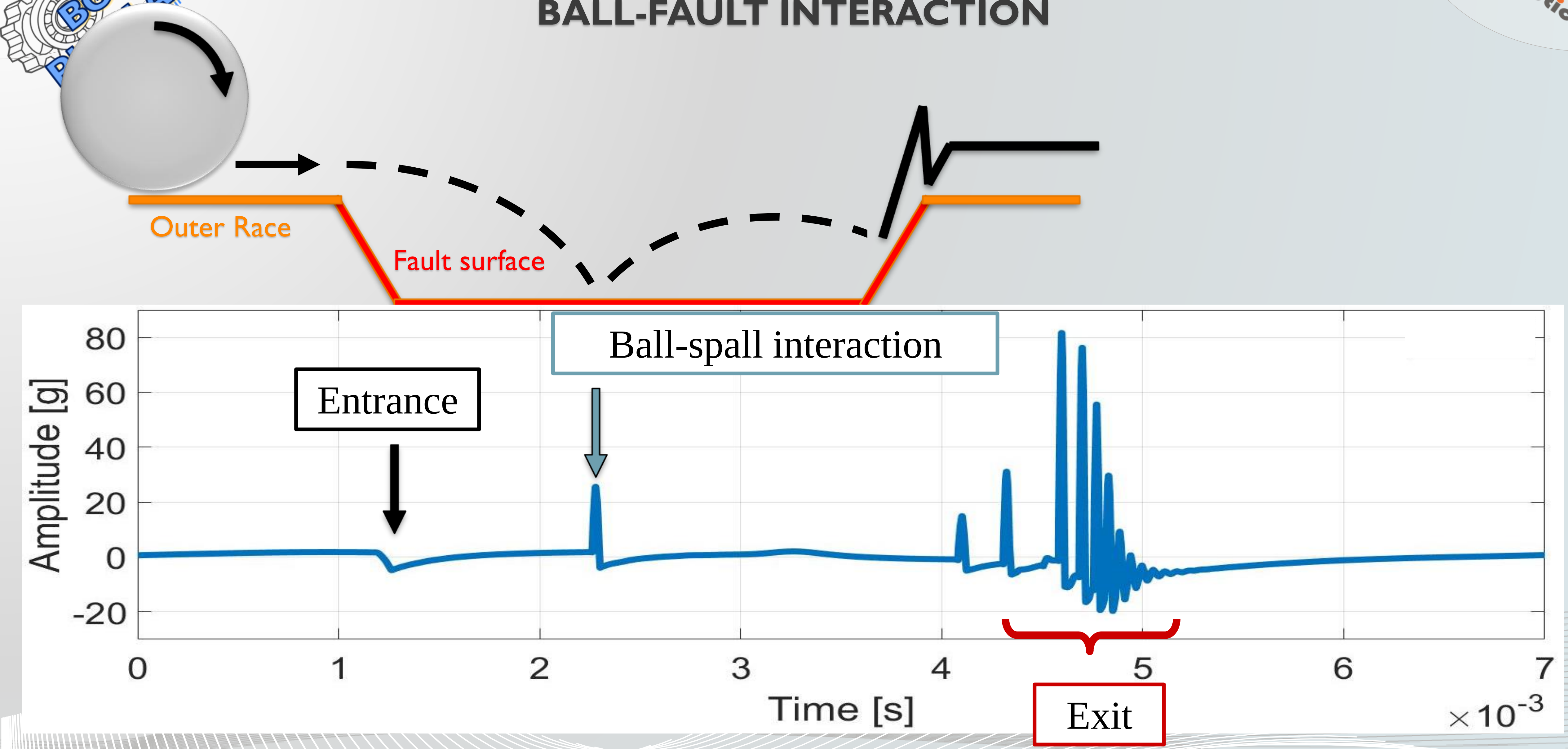

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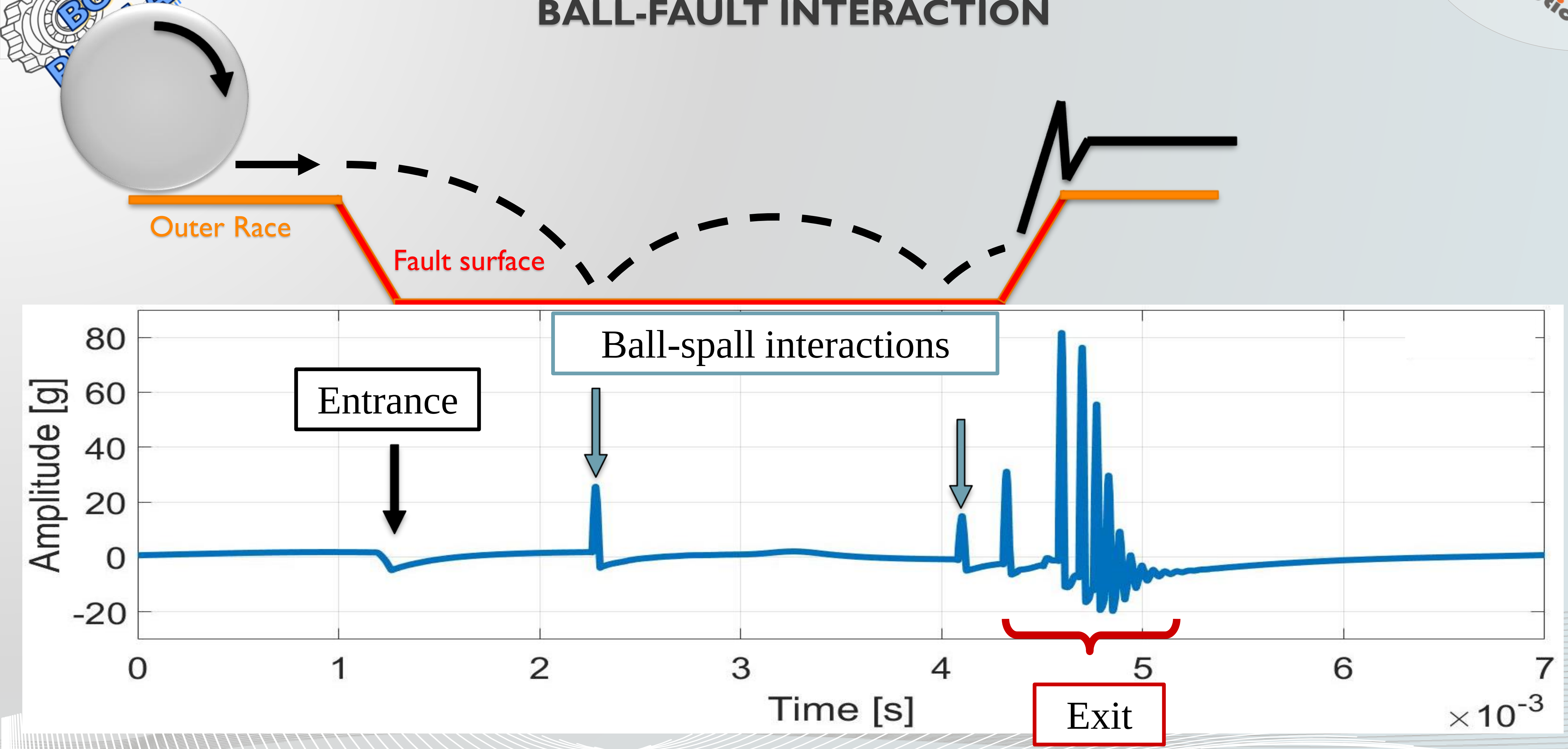
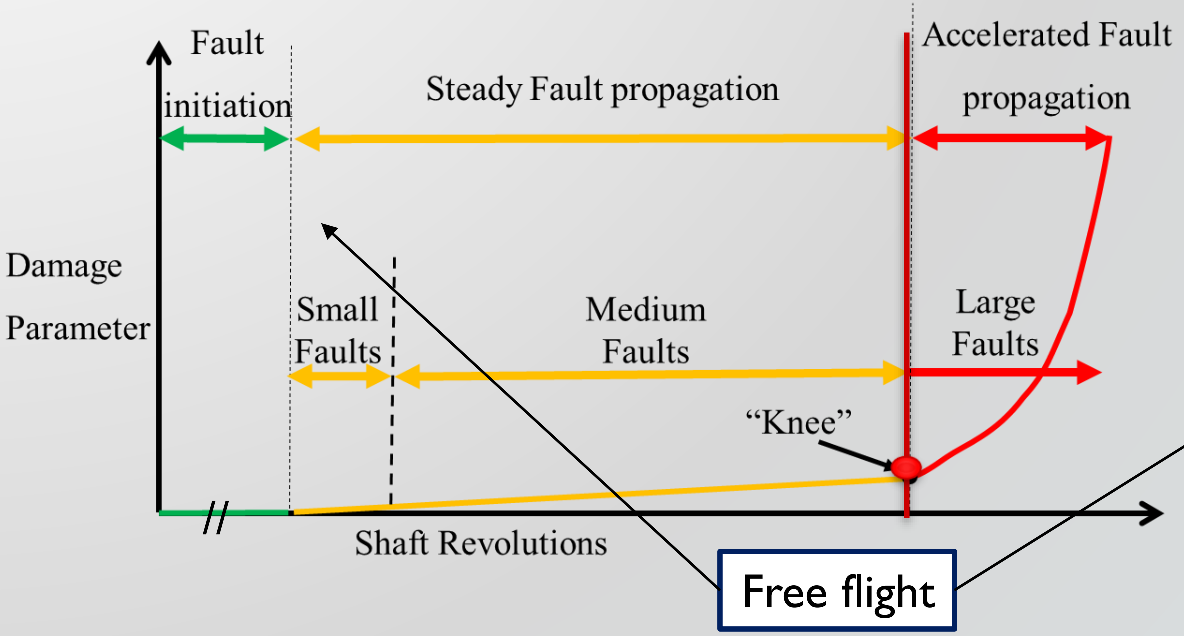
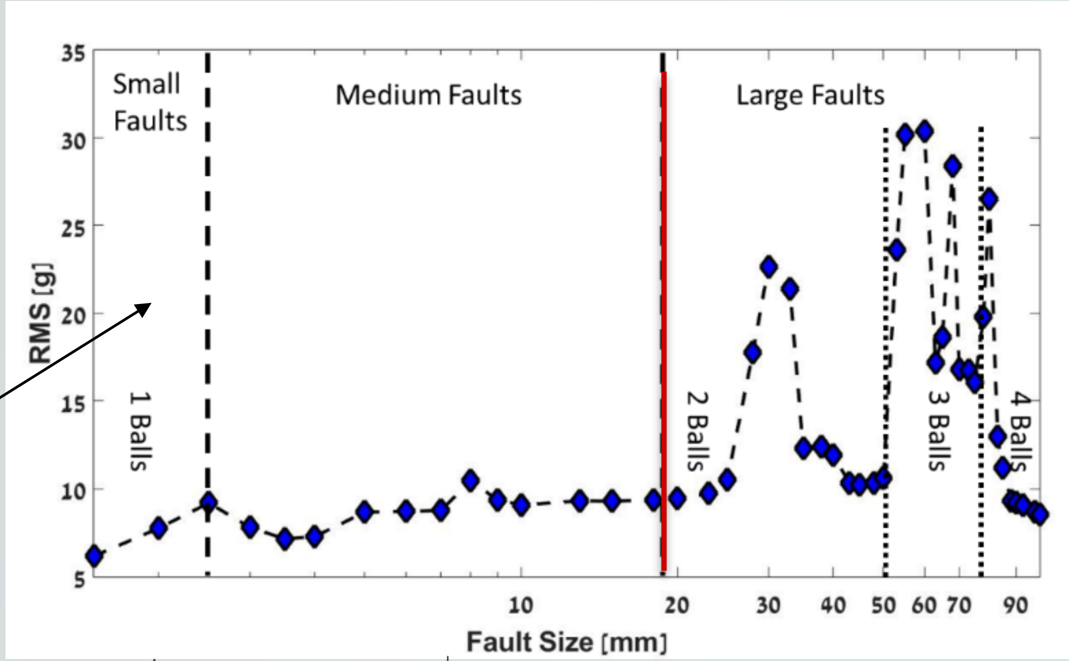
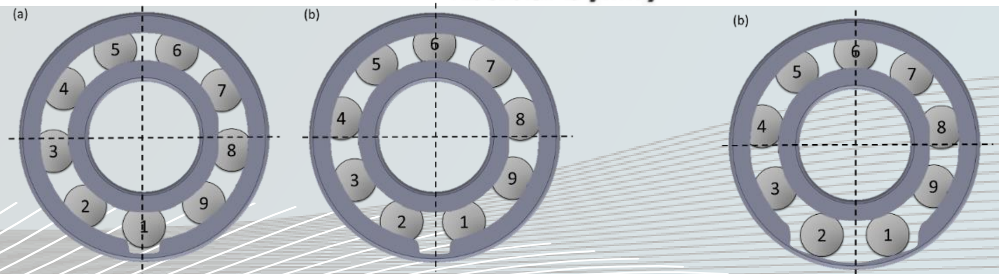


# BEARING DYNAMIC MODEL - INSIGHTS

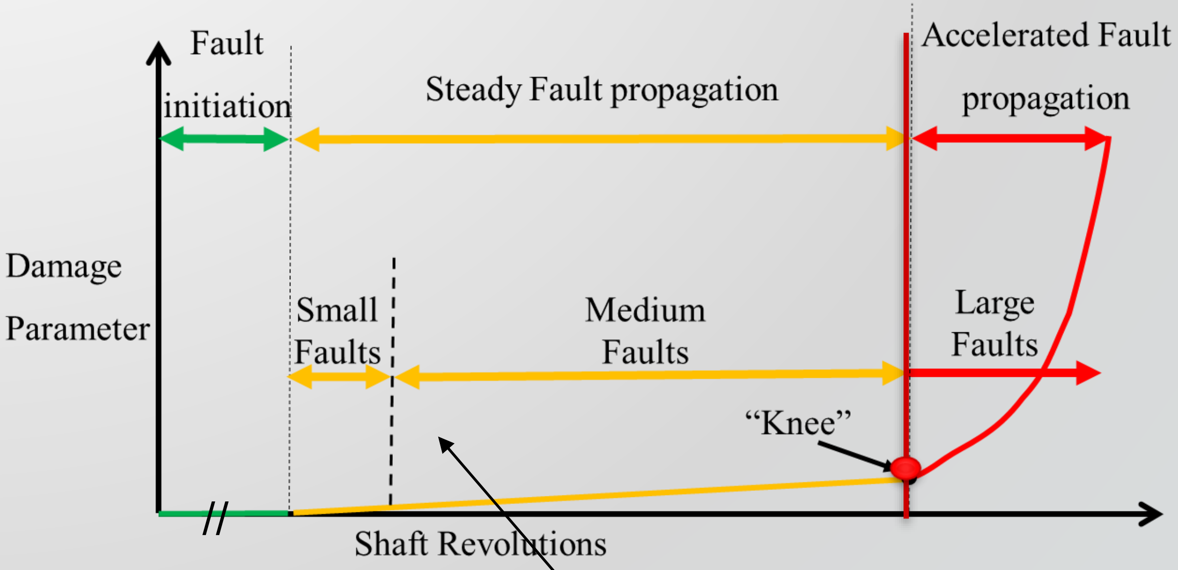


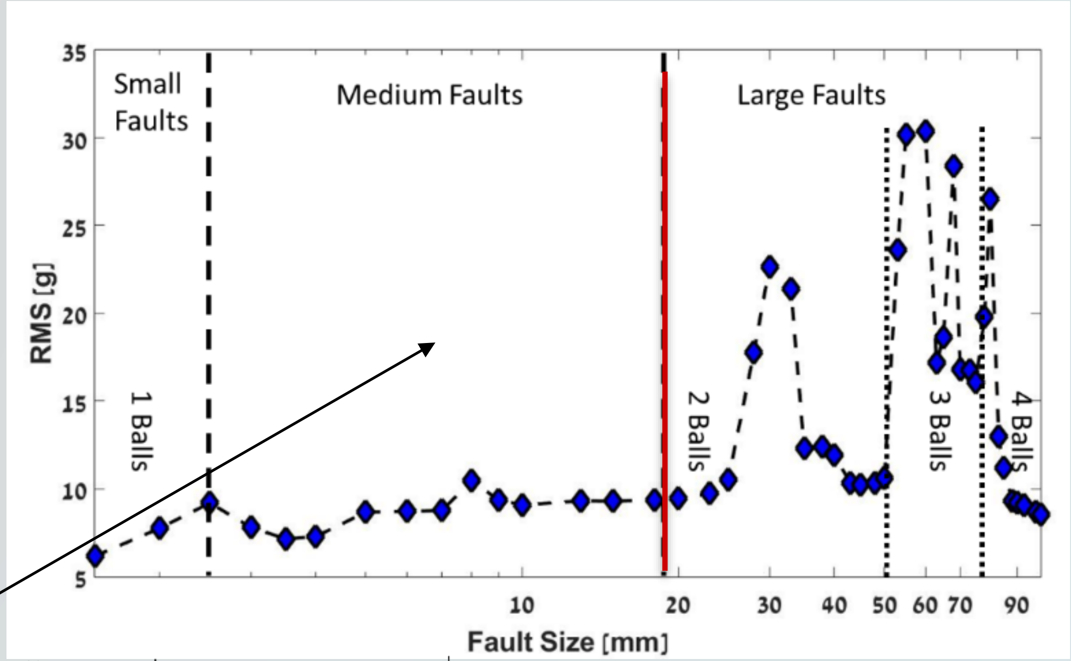



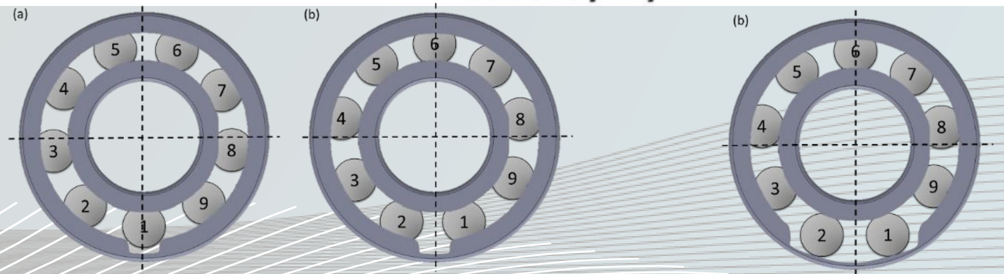
# BEARING DYNAMIC MODEL - INSIGHTS

- Classification of different spall severity stages and identification of critical spall size




1 ball in the fault



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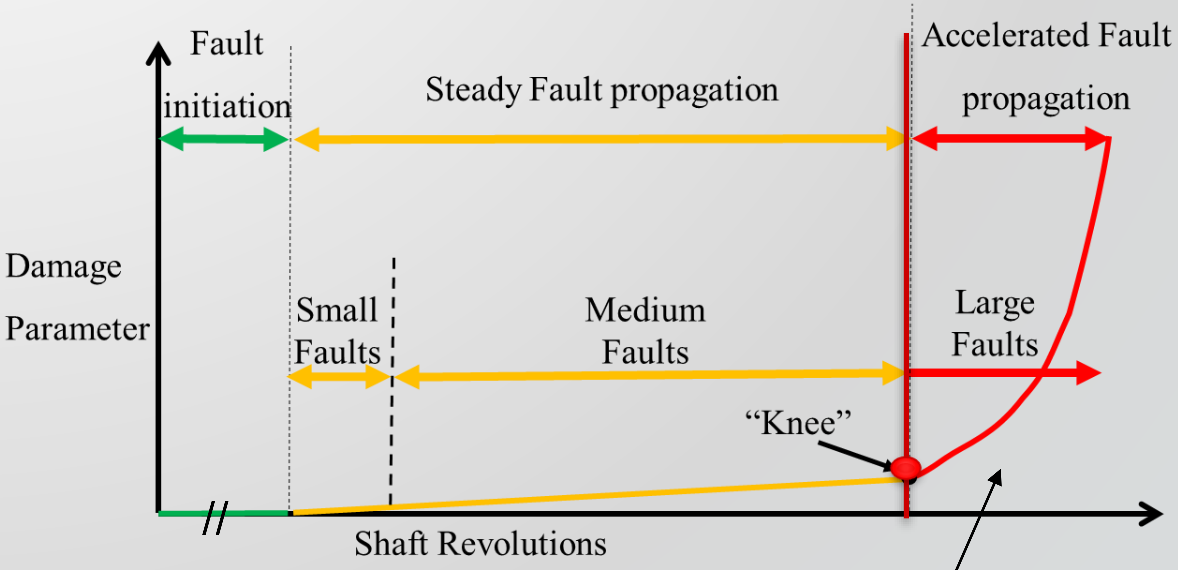
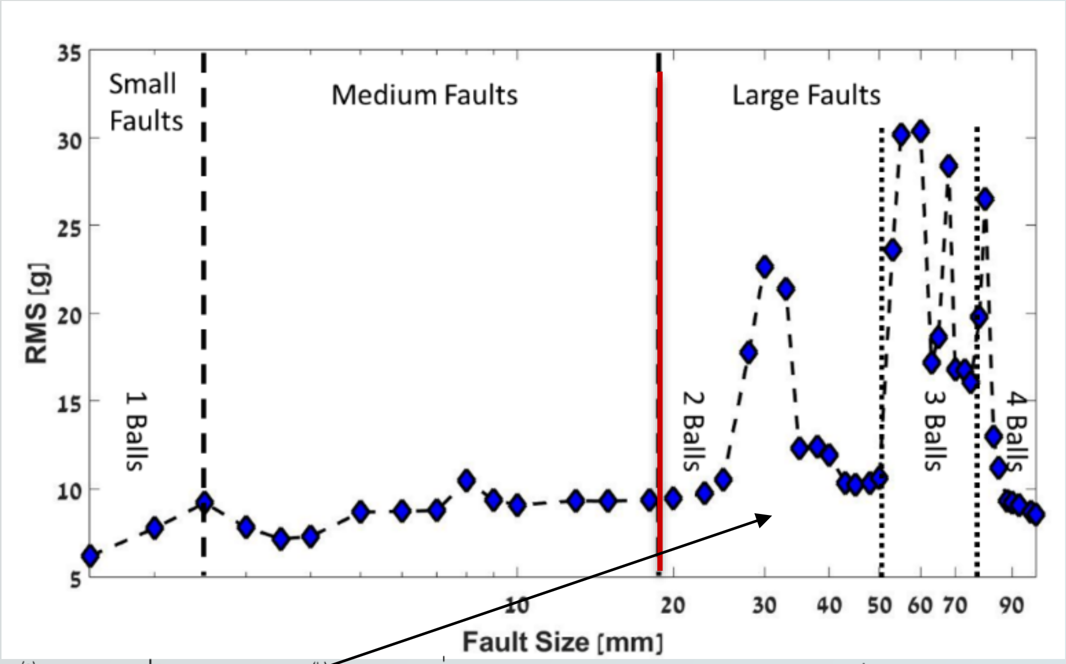
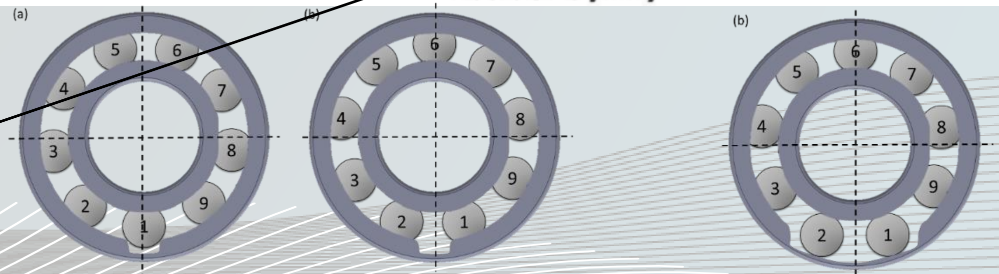


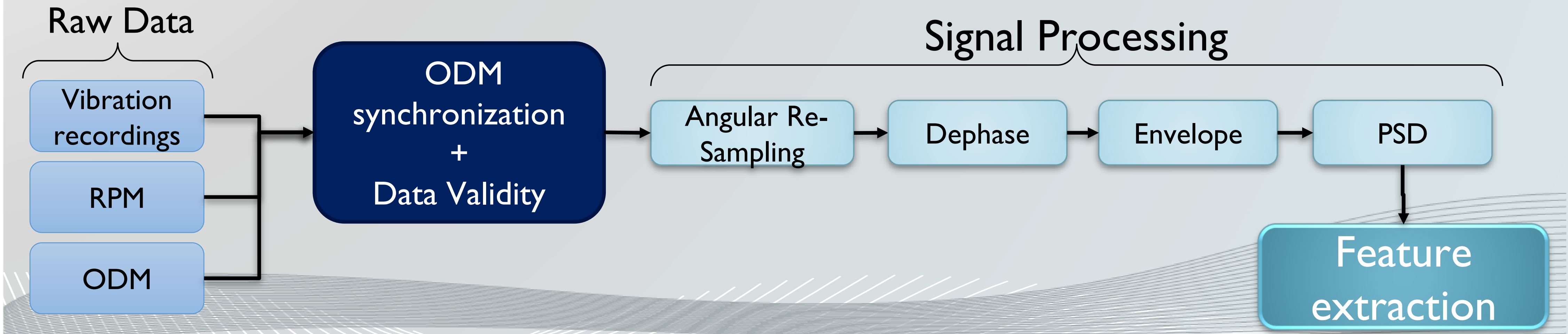



>1 ball in the fault

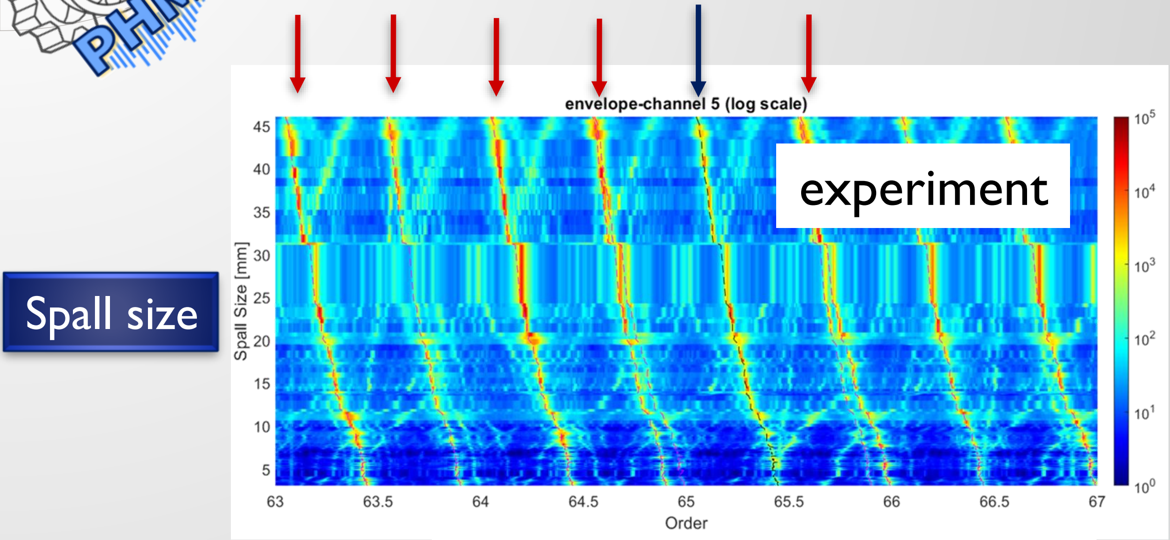
# VIBRATION ANALYSIS

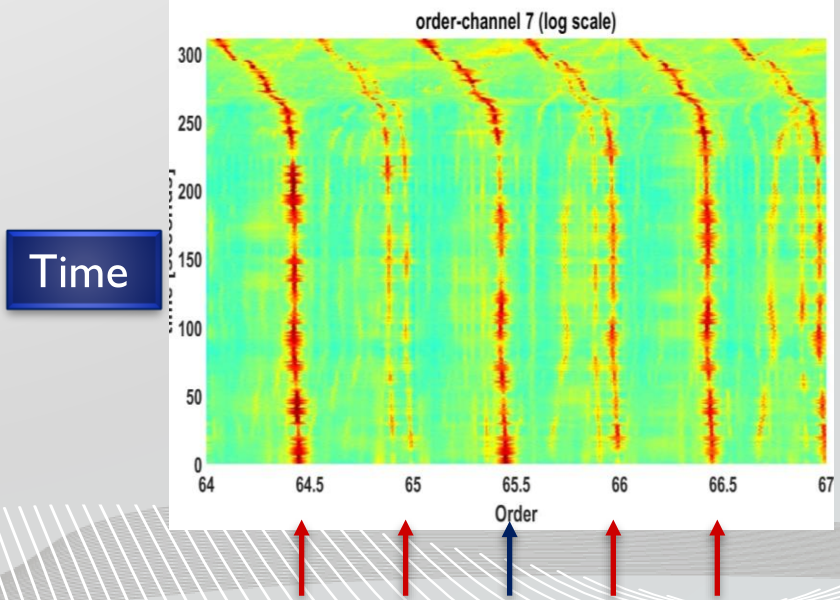
# Signal Processing

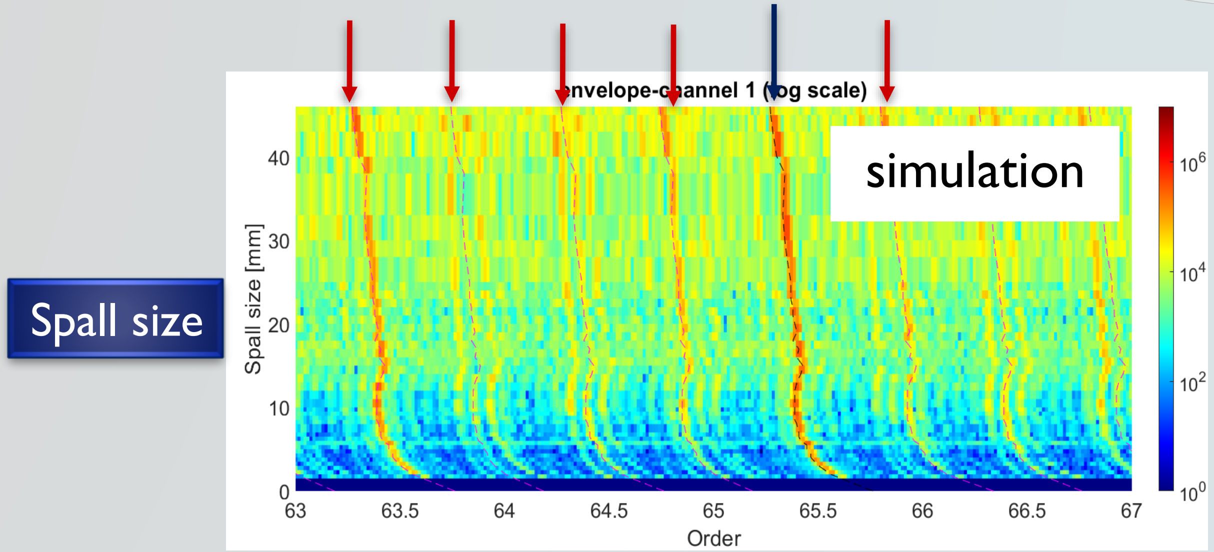
- Complete automatic algorithm
- Common processing for bearing signals
- Synchronization based on ODM recordings and automatic timestamping
- Advanced analysis for feature extraction



# SIMULATION AND EXPERIMENT



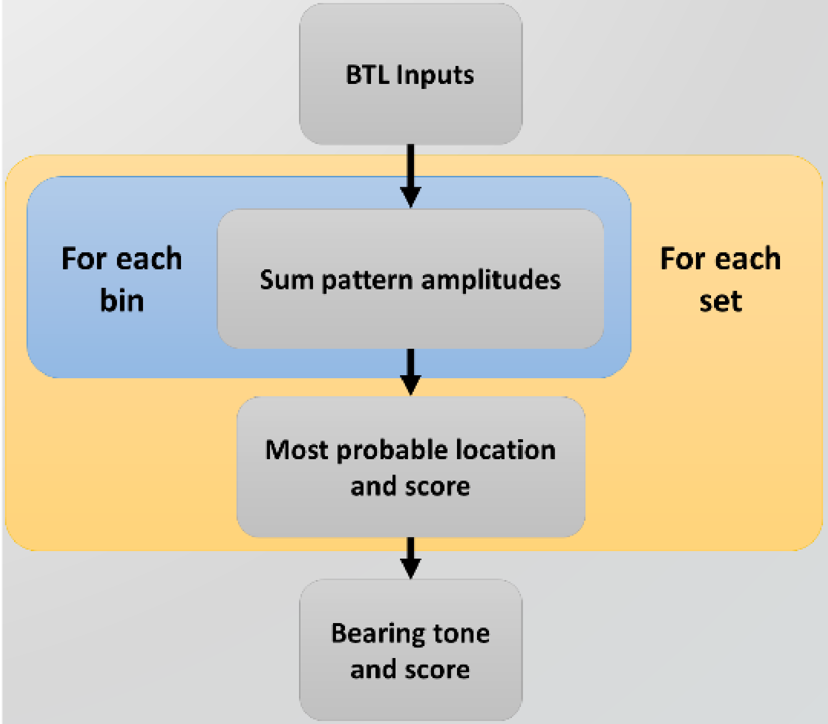

## Comparison between simulation and experiment

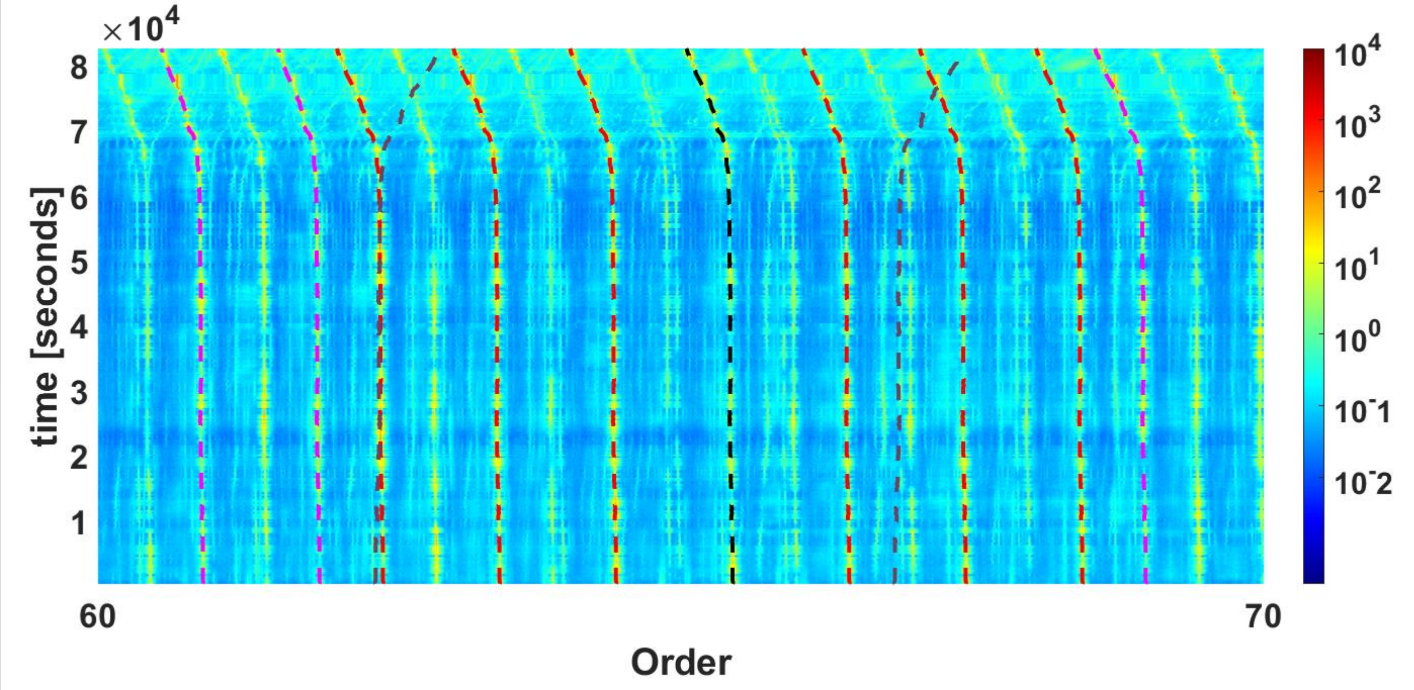
✓Bearing tones (BPFI )

✓Sidebands

# Bearing Tone Locator (BTL)

- BTL algorithm extracts the bearing tone location throughout the experiment



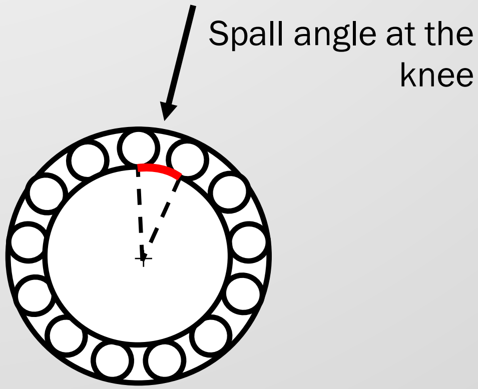



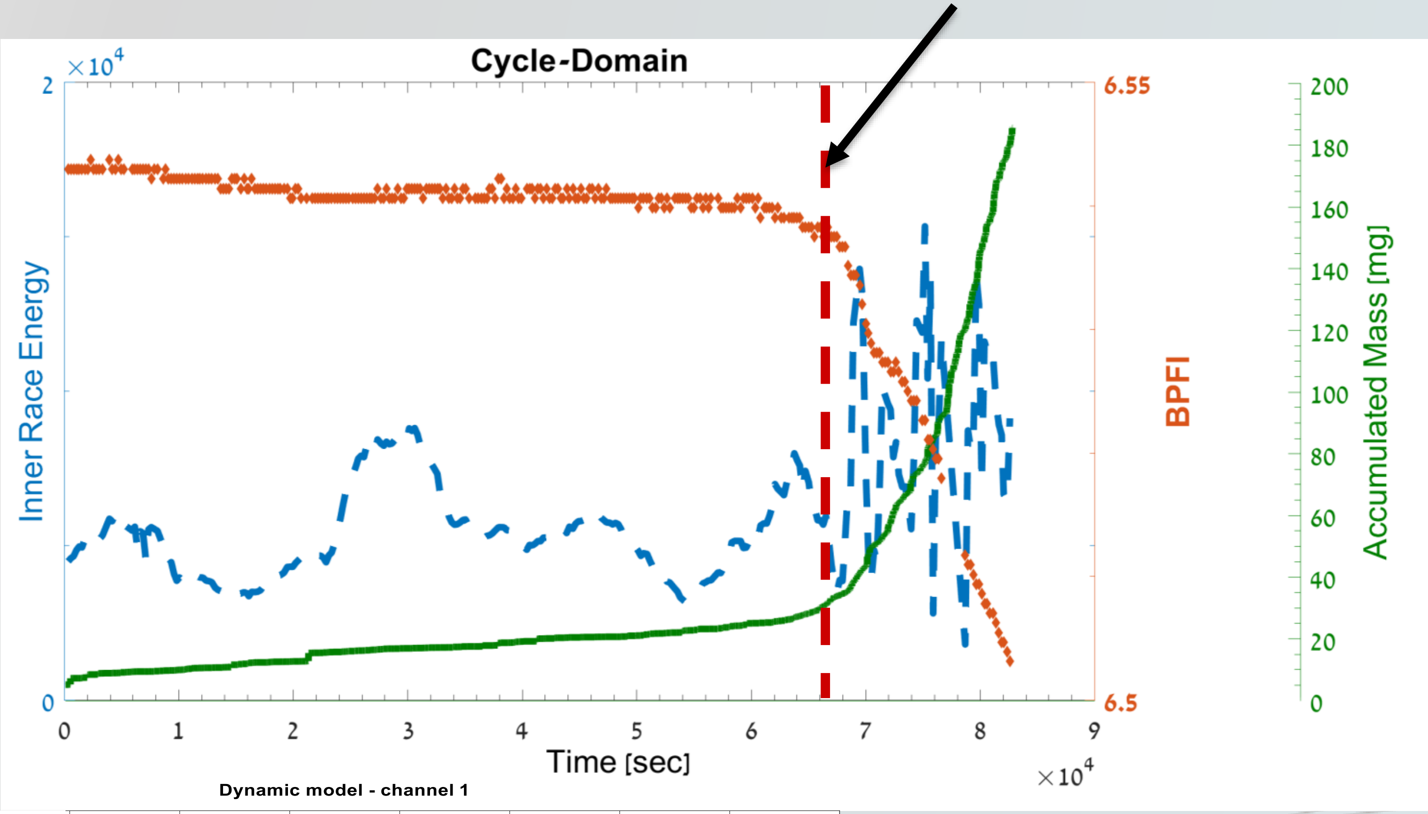

A. Sol, E. Madar, J. Bortman, R. Klein, "*Autonomous Bearing Tone Tracking Algorithm*", 2022.

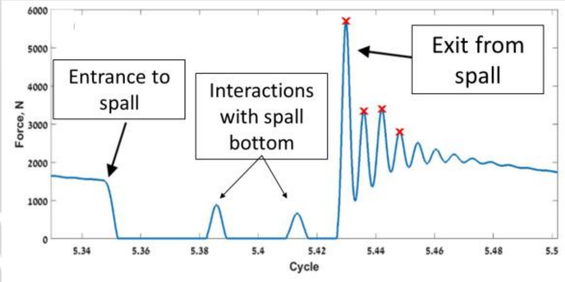
# CONDITION\SEVERITY INDICATORS

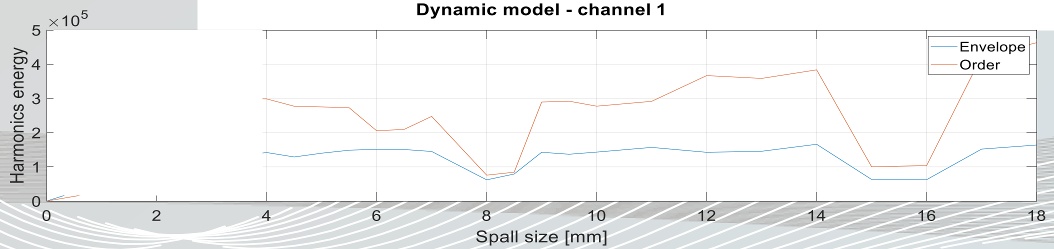
Three indicators were found to indicate the spall size of the knee

- ODM
- Energy
- Bearing tone



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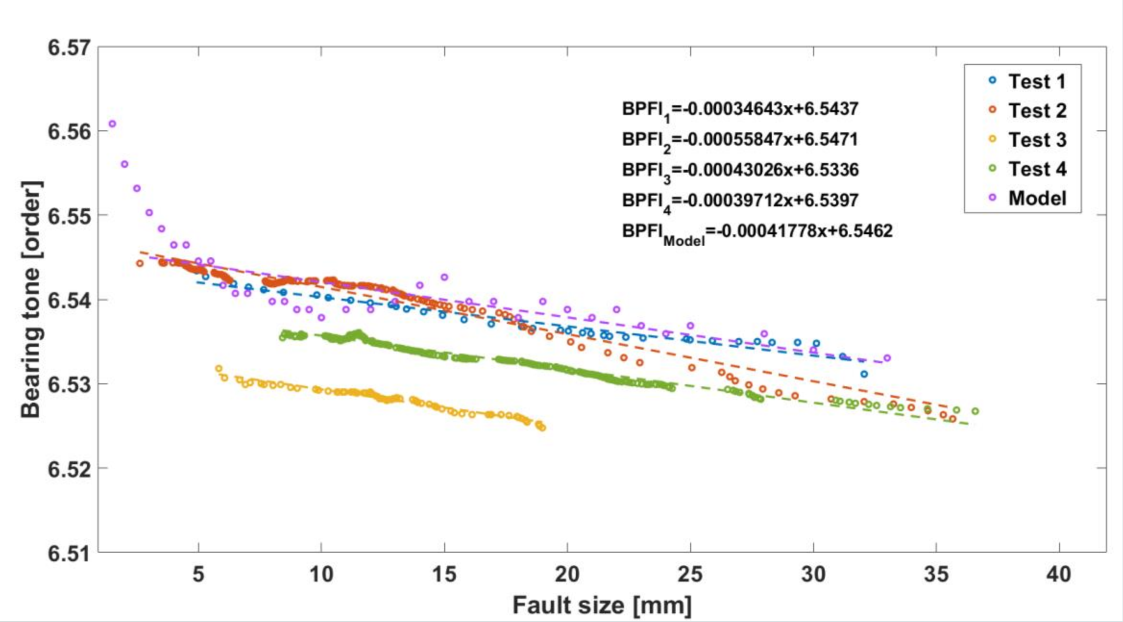
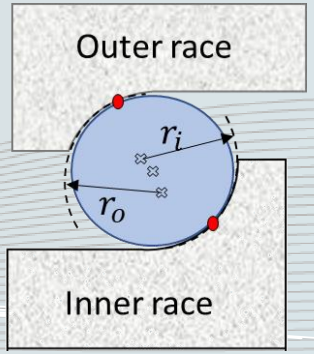
# CONDITION\SEVERITY INDICATORS

- Bearing Tone shift is a novel phenomenon
- Doesn't depend on the transfer function
- Correlates with the dynamic model
- Provides a constant linear trend for prognostics




Fault → Ball inside the fault does not carry load or resist movement → Other balls are loaded more / Inner race is free to move → Point of contact changes → Relative velocity between the Race and ball changes → Bearing tone changes



# Angular Contact Bearings – Summary

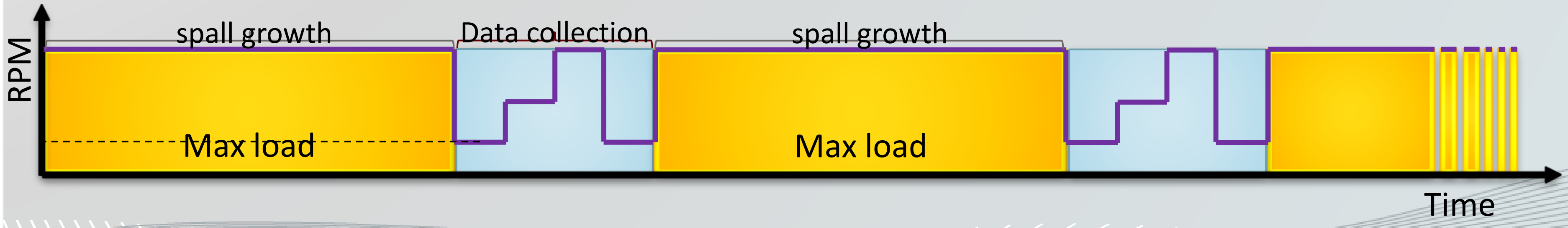
- The metallurgical analysis explained the spall's geometry at different propagation stages, enabling the ODM based severity estimation.
- Definition of the critical spall size at the knee (arc length between two adjacent balls) is based on the insights from the dynamic model.
- New condition indicators, independent of the transmission path, were developed:  bearing tone (BPFI) and mass loss
  - Prognostic capability was demonstrated based ODM data
- Energy variation caused by the ball interacting with the outer race was demonstrated in simulations of the dynamic model and it is under investigation

# ENDURANCE TESTS OF ROLLER BEARINGS

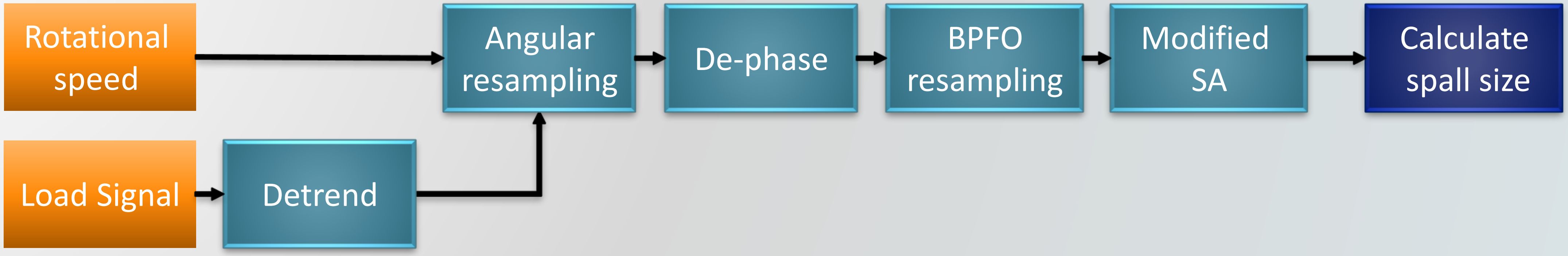
Severity estimation based on vibrations

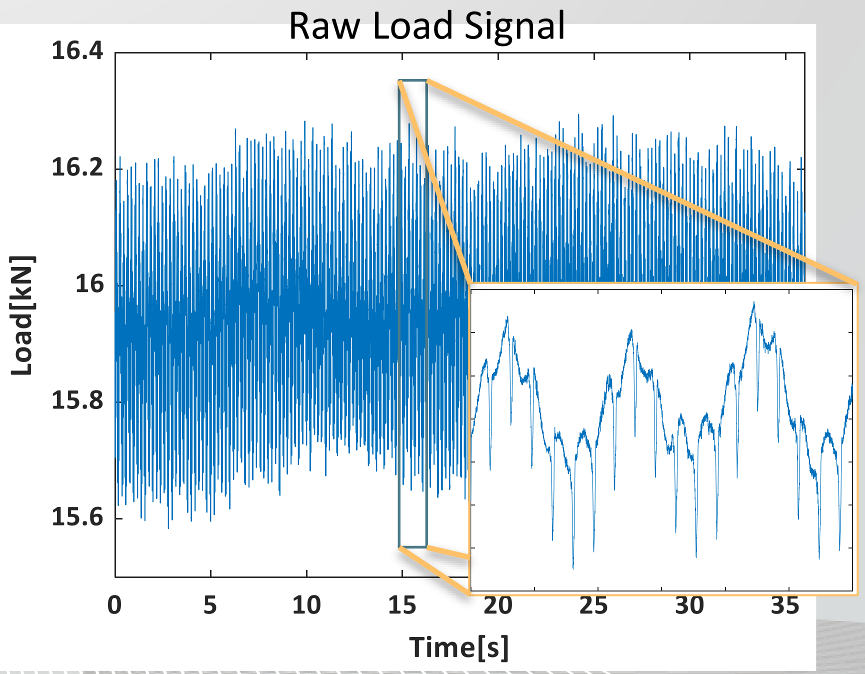
# Experiment setup

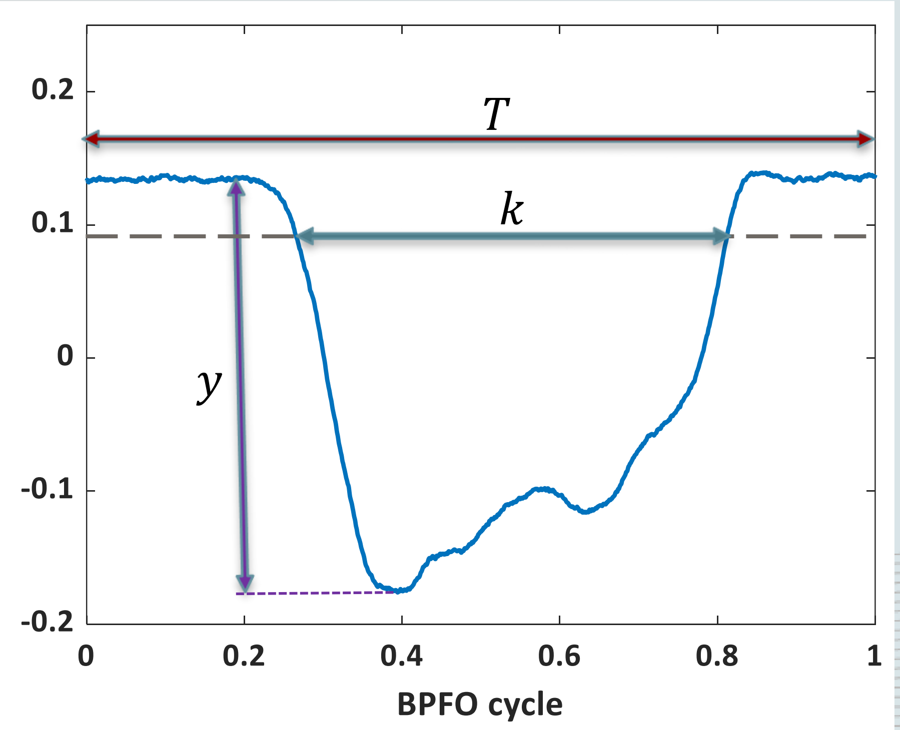
- Outer race spall growth on roller bearings endurance test. (70-300 MRev)
  - One experiment contains visual inspections (every 3 MRev)
- Measured Data: speed, load, acceleration
- The protocol consists of two stages.
  - The spall growth sections have high load and high rotating speed
  - The sections for data collection have different speeds (300-3000 RPM)




# LOAD ANALYSIS

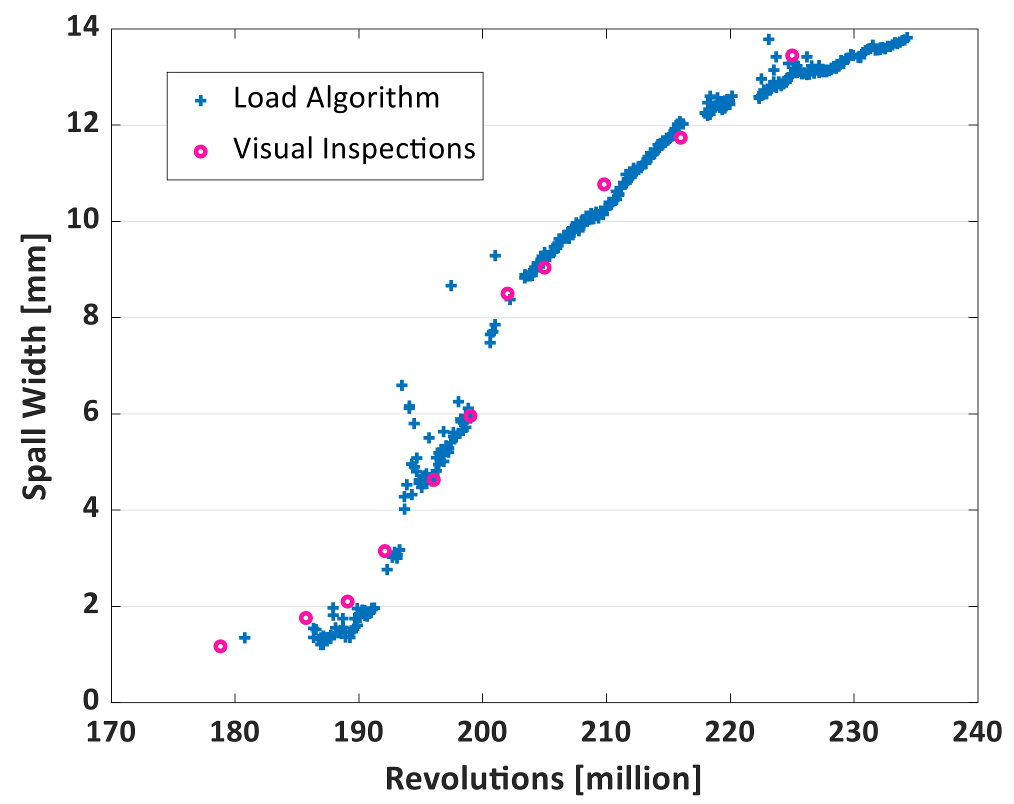


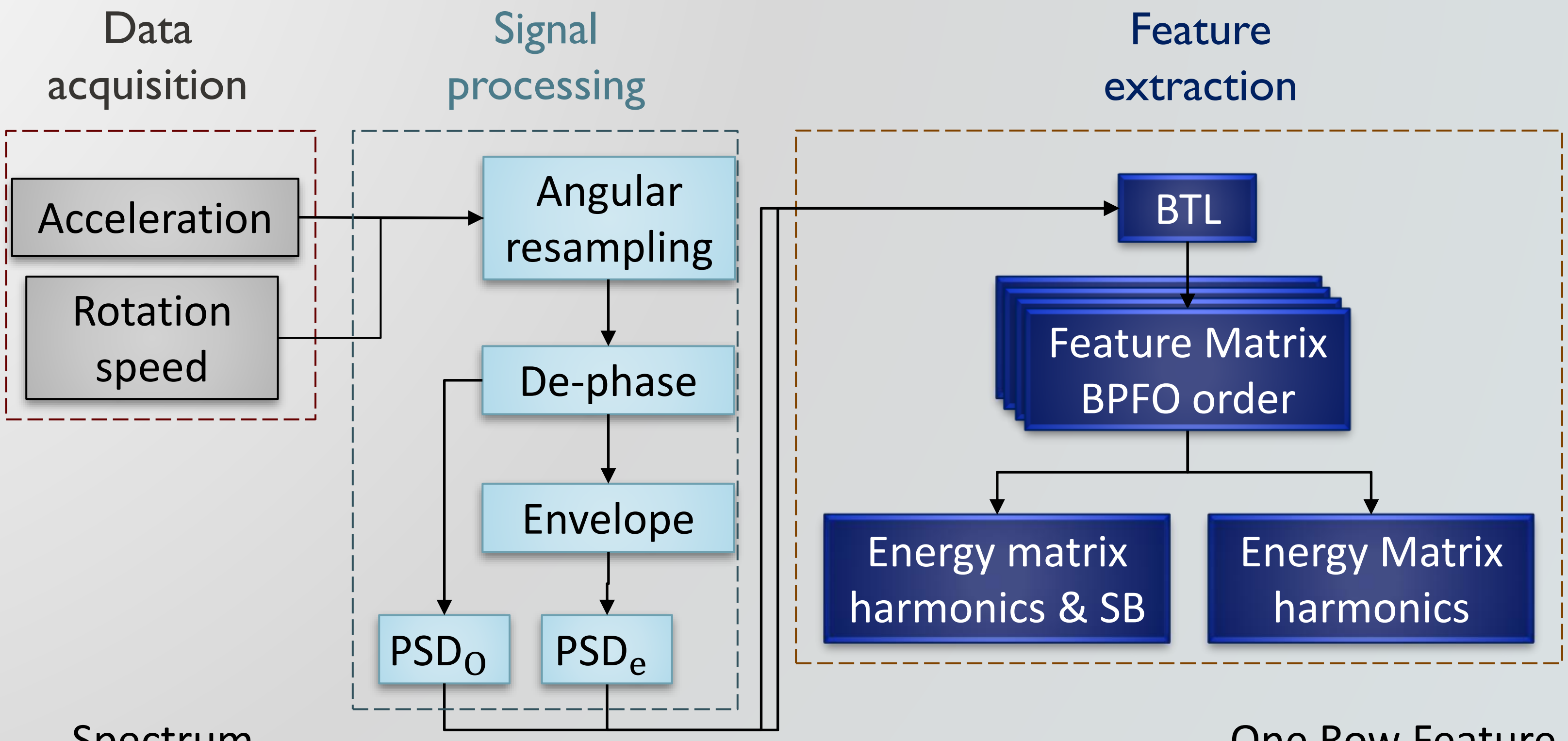



# Data Labeling

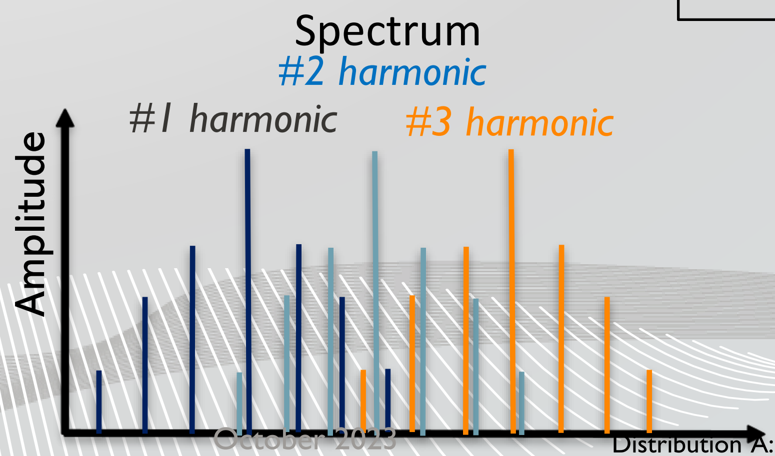
- The load signals collected at the minimum rotation speed and high load were analyzed  and validated by  the visual inspections (every 3 MRev) measurements
  - Recordings presenting a significant level only

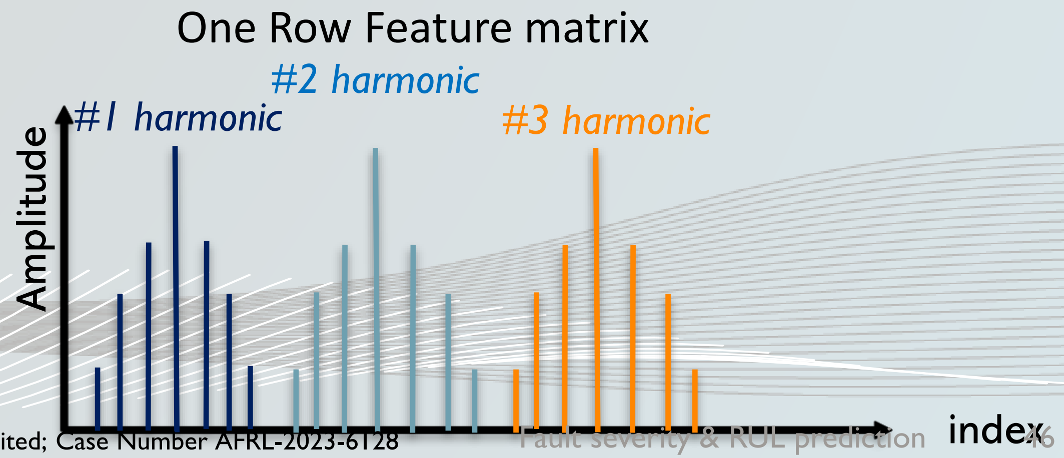


# SIGNAL PROCESSING & FEATURE EXTRACTION



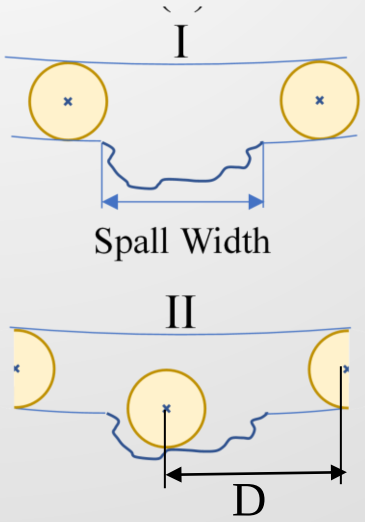

BTL- Bearing Tone Location algorithm

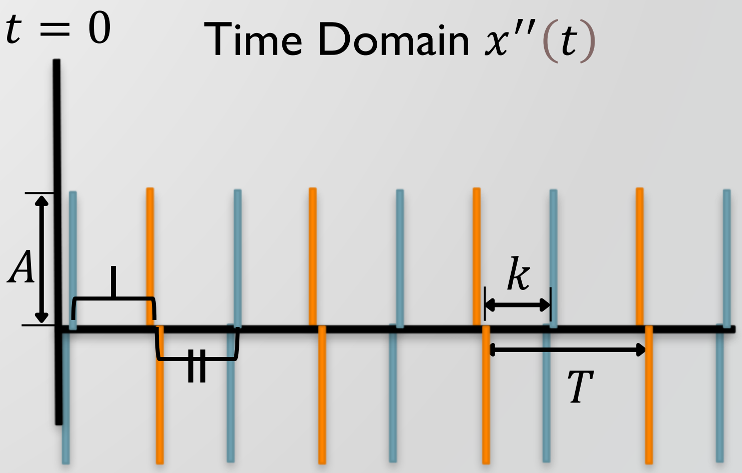


# THEORETICAL BACKGROUND

Roller bearings exhibit dual impulse behavior when encountering a spall



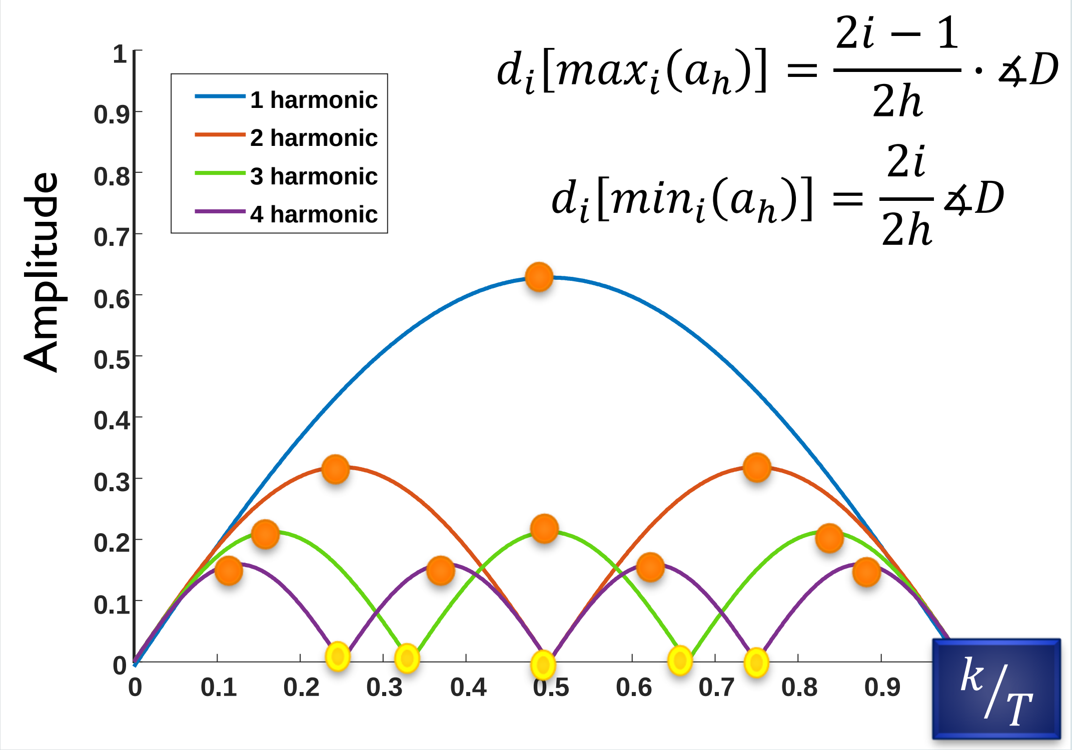

$k$ – lag of entrance to exit impulses

$T$ – time lag between 2 consecutive RE

$d = \frac{k}{T}$ spall length relative to RE distance

$$\mathcal{F}\{x(t)\} \rightarrow a_h = \frac{2A}{h\pi}|sin(\pi h d)|$$

$$\mathcal{F}\{x''(t)\} = (i\omega)^2 \mathcal{F}\{x(t)\}$$

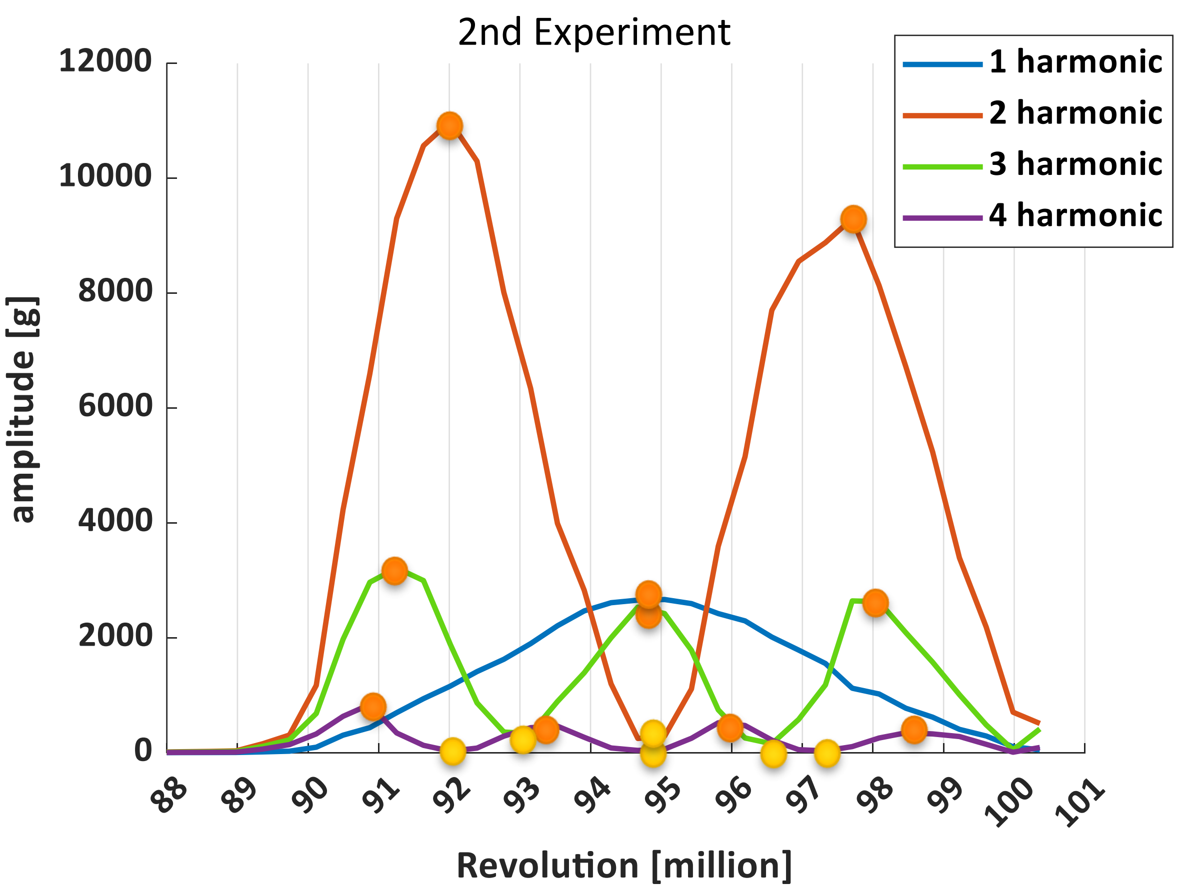


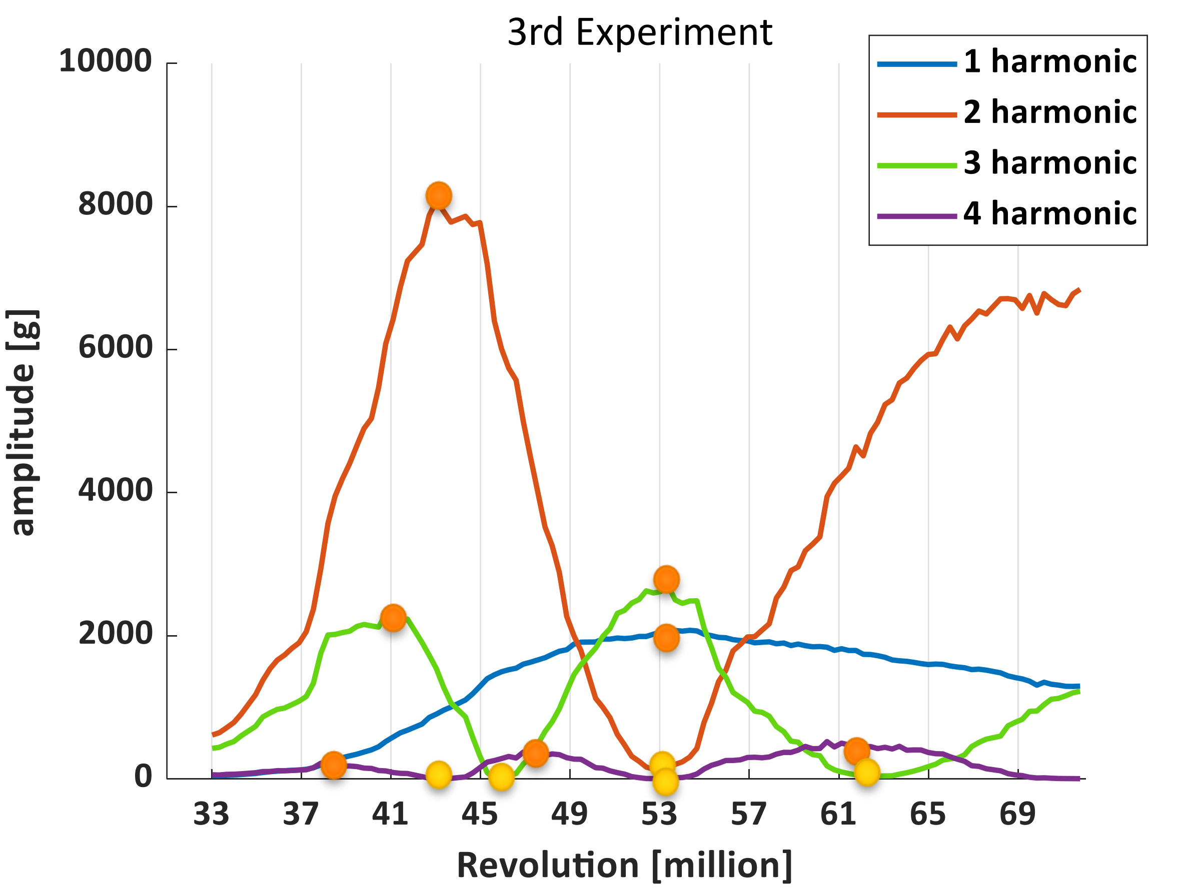

D – arclength between 2 RE

$d_i$ – i[th] maxima/minima time stamp

h – harmonic #

# TREND OF ENERGIES OF BEARING TONES HARMONICS



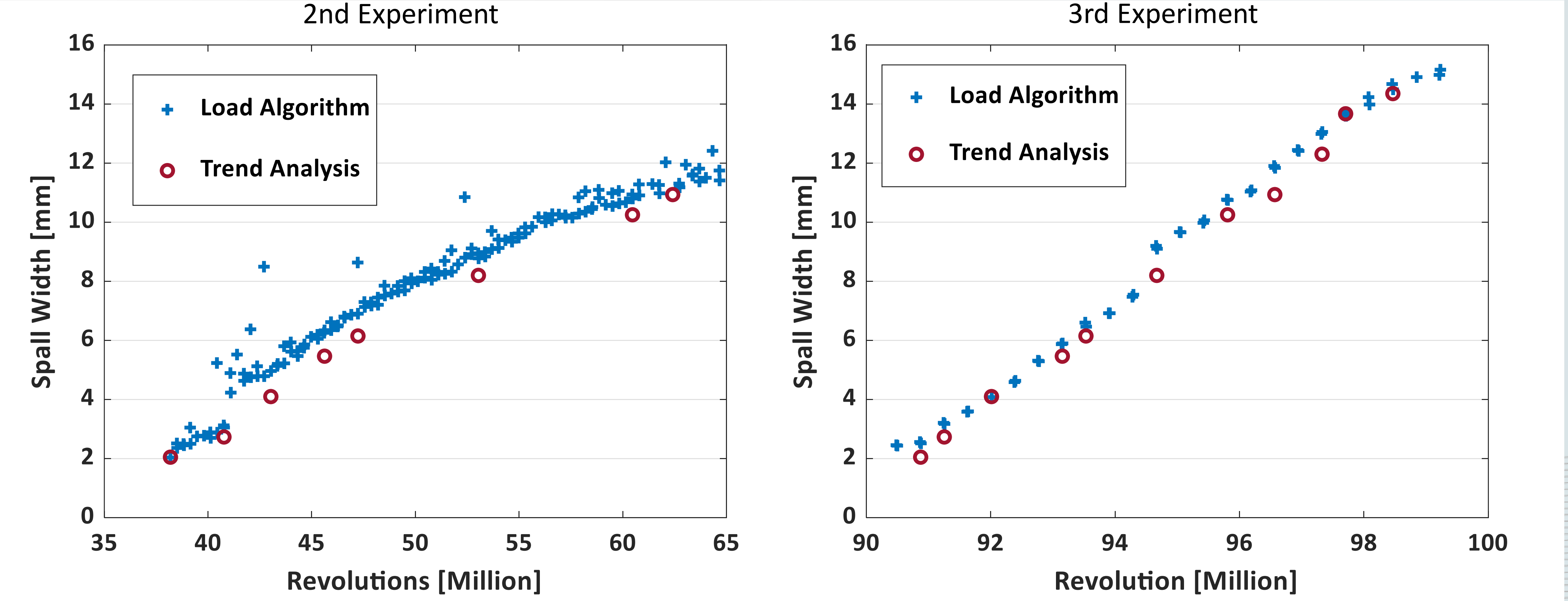




$$d_i[max_i(a_h)] = \frac{2i-1}{2h} \cdot \measuredangle D$$

$$d_i[min_i(a_h)] = \frac{2i}{2h} \measuredangle D$$

# RESULTS

New CIs, $d_i$, based on the trend analysis of the energies of the harmonics of the bearing tones represent the fault size/ severity



# Endurance Tests of Roller Bearings
## Summary

- Labeled database of endurance tests of roller bearings based on load algorithm was generated
- The new CIs, Maxima and Minima of harmonic trend indicate the spall size
  - Capable to track the severity
  - Independent of transmission path (machinery, operating conditions)

# QUESTIONS?