

# SnT 2023

CTBT: SCIENCE AND TECHNOLOGY CONFERENCE

HOFBURG PALACE - Vienna and Online

**19 TO 23 JUNE**

## **Failure Classification and Monitoring of Radionuclide Systems using State of Health (SOH) data**

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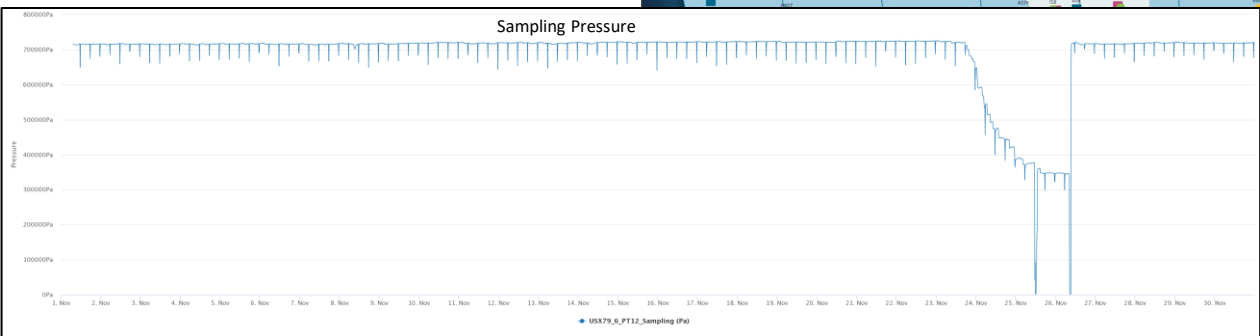
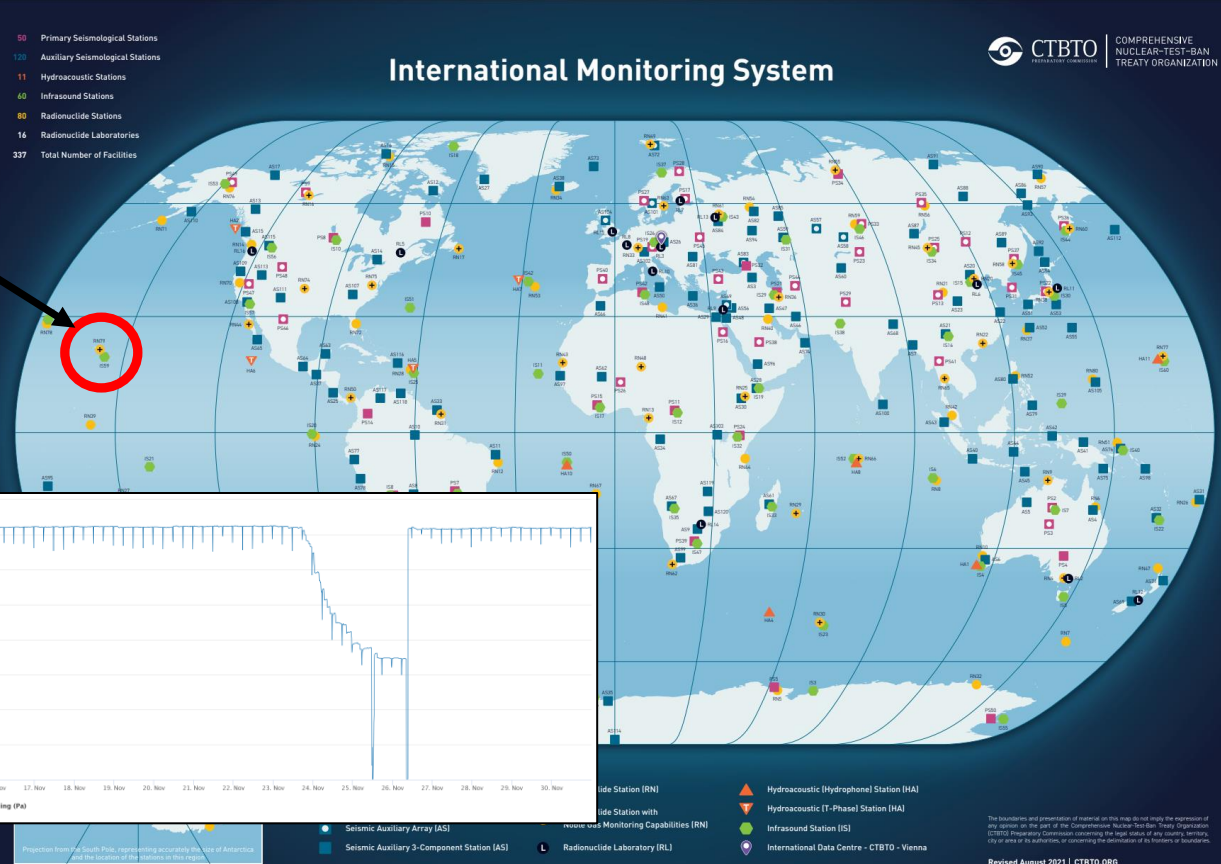
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PNNL-SA-186048

# Failure at RN79

In November of 2020 the SAUNA at IMS station RN79 had a Membrane Dryer Failure



Projection from the South Pole, representing accurately the top of Antarctica and the location of the stations in this region.

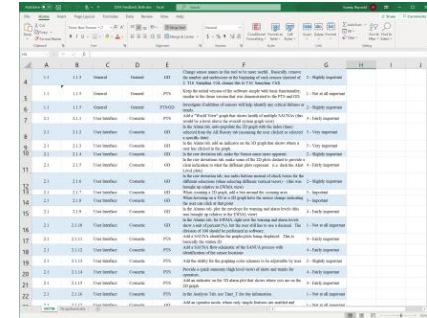
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## GOAL: Detect and classify system failures before they occur

### • How do we get there?

- Engage operators and experts to leverage experience and help understand the needs in monitoring
- Develop State of Health (SOH) monitoring tools that are scalable and system agnostic
- Develop tools capable of using both basic and advanced algorithms for both diagnostics and prognostics
- Leverage latest advancements in data science that may use data-driven and physics-based models to identify and predict failures with the current available SOH data
- Identify where there are data gaps and identify sensors to provide critical information needed *strategically* monitor components
- Develop data science algorithms around new strategically selected sensors
- Translate algorithms to operations



Feedback from GD/PTS used to design SOH architecture and user interface

- Radionuclide systems can have hundreds of sensors associated with the processing
- All sensors are sampled on some internal interval
- Internal SOH sensor data is typically used for providing system alerts
- A subset of the sensors are sampled in 10-minute intervals and sent in 2-hour files to a data center
- Sensor data examples are:
  - Pressure
  - Temperature
  - Flow Rate
  - Voltage
  - Current
  - Processing state
  - Source state
  - Valve state
  - Gas Concentration



SAUNA-III



RASA



Xenon International



SPALAX-NG

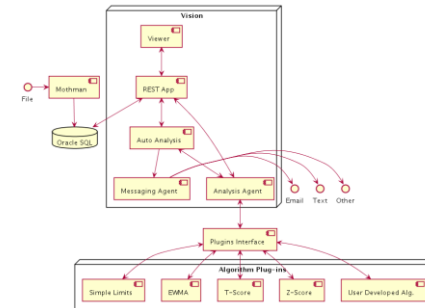
## Engaging Operators & Experts

- PNNL worked closely with U.S. IMS operator, General Dynamics (GD) for feedback on SOH and requirements
- PNNL also engaged the Provisional Technical Secretariat (PTS) for feedback

## SOH Analysis Architecture

- Modular approach taken, that is system agnostic and allows for multiple algorithms to be used for analysis
- Algorithms can be run in parallel
- Sensor lists are built dynamically
- Currently uses Oracle SQL database, but compatible with other database formats (PostgreSQL)
- Standard interface for analysis algorithms
- Standard interface for data sources (IMS2.01)
- Web-based graphical user interface
- Software developed in Java
- *Uses Representational State Transfer (ReST) architectural style*

Feedback used to design SOH architecture and user interface



SOH architecture implementation

# Scalable Architecture and Browser

The image displays four distinct scientific equipment units, each with a corresponding monitoring software interface:

- SAUNA:** A white industrial cabinet. The software interface shows a graph of periodic pulses and a control panel with buttons for 'Temp & Oven B', 'GC', 'Pressure: Helium Bottle', 'Pressure: GC Reference Gas', 'Pressure: Carrier Gas IN', 'Pressure: Oven B MS Out', and 'Pressure: Sampling'.
- SPALAX:** A grey industrial cabinet. The software interface shows a graph of periodic pulses and a control panel with buttons for 'Auxiliary Status', 'Room Temp', 'MultiStatus', 'UPS Status', 'walpLab', 'dort1', and 'High Voltage'.
- Xenon International:** A black industrial cabinet with a screen. The software interface shows a graph of periodic pulses and a detailed data table with columns for 'Line', 'Name', 'Unit', 'Status', and 'Value'.
- RASA:** A black industrial cabinet with its door open, revealing internal components. The software interface shows a graph of a noisy signal and a control panel with buttons for 'Blower Temperature', 'Chiller Temperature', 'CPU Temperature', 'UPS Temperature', 'UPS Time Remaining', 'Blower Current', 'Chiller Current', 'UPS Load Power', 'UPS Battery Capacity', 'UPS Voltage', and 'Uncategorized'.

- This research is focused on strategically identifying sensors to monitor critical system components
- Research also includes development of related electronics to read out and perform some measurement analysis in real-time
- Recent testing
  - A current transducer, temperature, and accelerometer were used for monitoring a vacuum pump used in a system
  - Read-out electronics were developed for testing
  - Data was collected under different configurations for analysis
  - Fast-Fourier Transform (FFT) of the accelerometer calculated on-board for easier processing

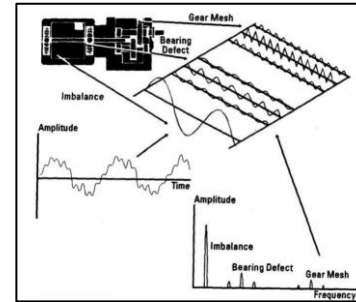
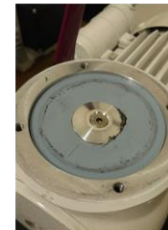
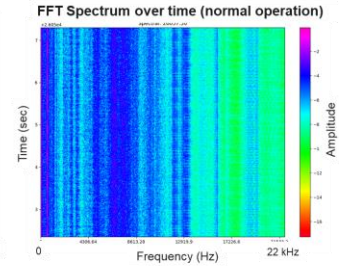
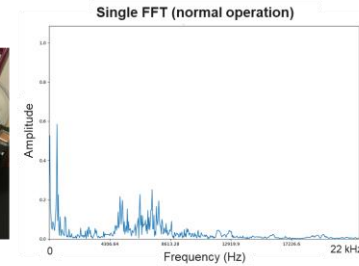


Diagram highlighting frequency components from a motor

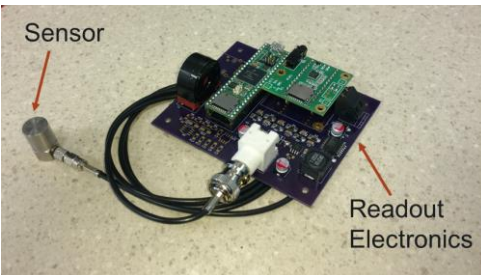
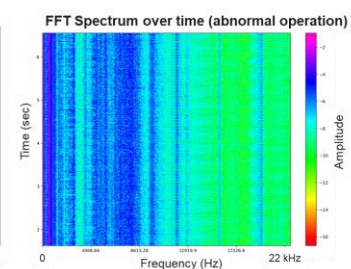
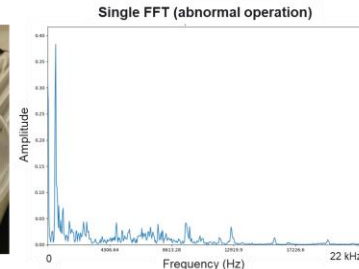
*Fundamentals of Vibration  
 Measurement and Analysis Explained  
 - Peter Brown*



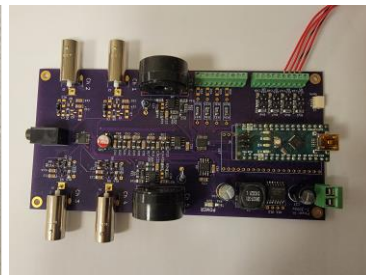
Normal operation of a pump with a good diaphragm



Operation of the same pump with a ruptured diaphragm

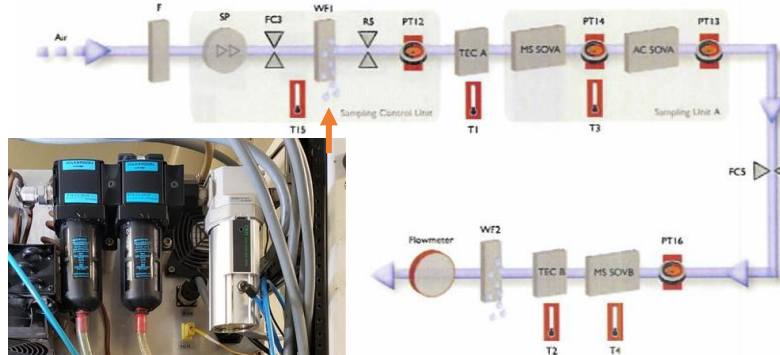


Accelerometer and readout circuit board

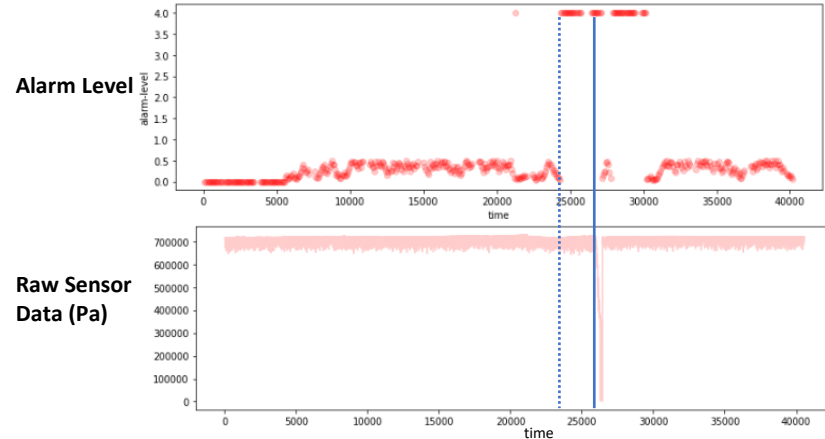
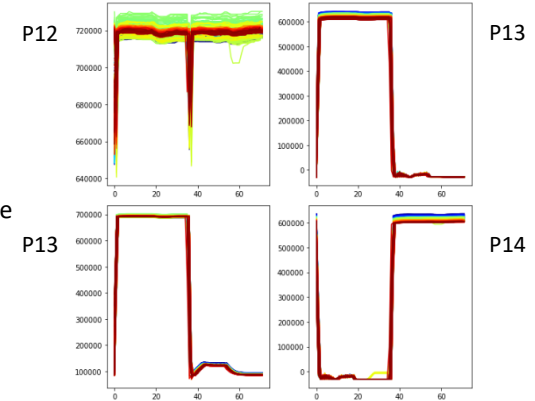


Multi-input board for small sensor testing

- Working with GD to identify critical failures
- We are testing failure prediction algorithms that use these features with our small set of labeled hardware failures
- Going back to the RN79 Membrane Dryer Failure
  - The minimum pressure captured by P12 halfway through an analysis cycle
  - The increase in room temperature during an analysis cycle
- Using an alarm level based on a *Multi-Scale Rank Permutation Change Localization* technique (Eklund, Hu)
- Alarm based on P12 precedes onset of failure by about 8 days

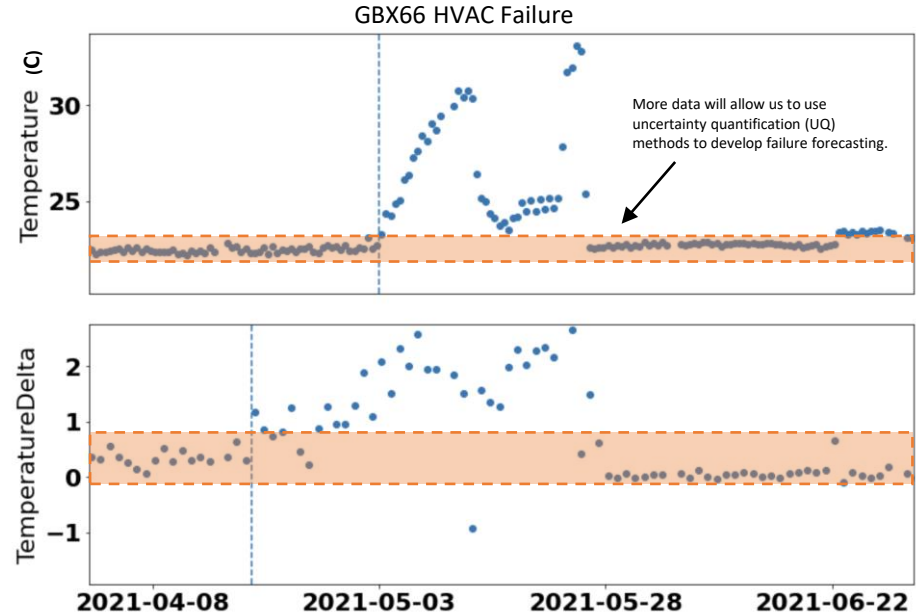


Four SAUNA Pressure sensors arranged to align with analysis cycle





- Using sensors that already exist, the team is performing critical failure identification
- Increase in temperature during a cycle may be an early indicator for HVAC failure (right)
  - Easy to distinguish from a membrane dryer failure, which is based on P12 pressure values
- We will need more labelled failures to develop UQ and failure forecasting



- We will continue to combine detailed studies of failures with modern ML anomaly detection tools like generative networks and transformer models to develop **interpretable** failure forecasting



Station GBP66



HVAC at GBP66

## Summary

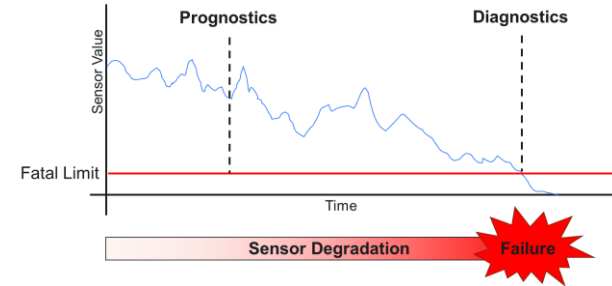
- PNNL working with experts and leveraging feedback to develop new tools
- A framework was developed to ingest and analyze SOH data that is system agnostic
- New sensors being researched to fill data gaps
- Algorithms for early detection and classification started



New sensors can provide critical data for predicting failures

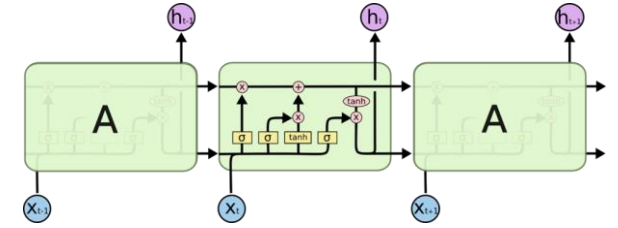
## Moving Forward

- Investigate sensor groups to not only provide alerts, but identify the source of the failure
- Continue sensor research
- Use multiple sensors to correlate failures to help with predictions (explore the entire feature space)
- Explore integrating environmental conditions into algorithm research (i.e. cabin temperature, humidity, etc.)
- Translate algorithms to operations

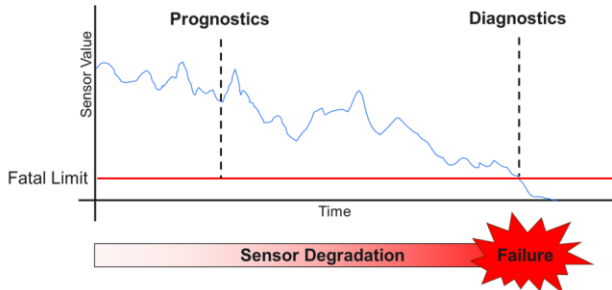


Thank You

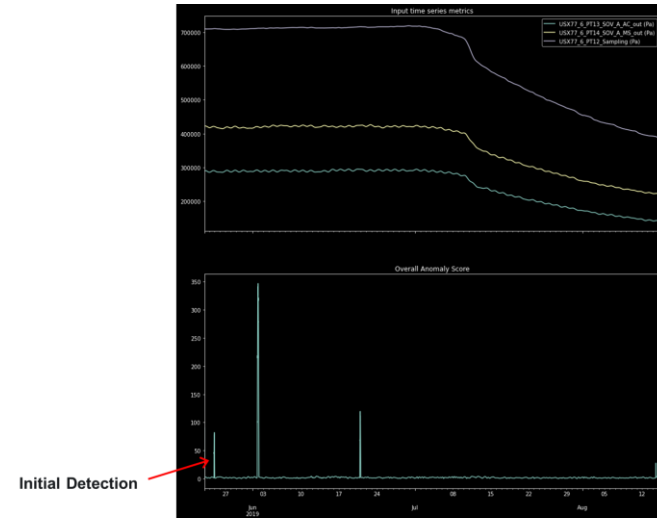
- Exponential Moving Weighted Average (EWMA)
- Linear Regression
- Long Short-Term Memory (LSTM)
- Koopman Decomposition
- Robust Statistics Detector
- Multivariate Anomaly Detector
- Cumulative Sum Detector
- Bayesian Online Changepoint Detection (BOCP)
- Multi-Scale Rank-Permutation Change Localization



LSTM model with layers to model the temporal data



\*Inspired by Mechanical Systems and Signal Processing "Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications" (Jay Lee, Fangji Wu, Wenyu Zhao, Masoud Ghaffari, Linxia Liao, David Siegel, 2014)



Using the Multivariate Anomaly Detector on three pressure sensors, PT12, PT13, PT14

# Wide Variety of Algorithms and Methods to Explore

## Algorithm

## Uses

Time Domain Analysis	Directly uses waveform to compare different signals
Fourier Transform	Analyze data in frequency domain
Short-time Fourier Transform (STFT)/Wigner–Ville Distribution (WVD)	Analyze signals in time and frequency domain
Wavelet/Wavelet Packet Energies	Represents time signals in terms of finite length or fast decaying oscillating waveform
Hilbert–Huang Transform (HHT)	Decompose complicated signals into finite number of intrinsic mode functions
Principal Component Analysis (PCA)	Reduce dimensionality by transforming original features into new set of uncorrelated features
Fisher Linear Discriminant	Reduce dimensionality by seeking a projection that best separates the data in a least squares sense
Gaussian Mixture Model (GMM)	Density model which comprises a number of Gaussian functions which are combined
Logistic Regression (LR)	Find the best fitting model to describe the relationship between inputs and outputs
Statistical Pattern Recognition (SPR)	Calculates the overlap between the current feature distribution and the normal mode
Gaussian Process Regression/Prediction	Fit models to data and perform prediction with Gaussian
Particle Filter	Bayesian approach to obtain state estimation
Kalman Filter	Bayesian technique that estimates state of a process and minimizes covariance estimation
Feature map pattern matching (Self-organizing Maps)	Represents multidimensional feature space in a low dimensional space
Bayesian Networks	Directed acyclic graph tool to present the structure of conditional interdependency relations and probability distributions between variables
Neural Network	Can learn the knowledge by modeling complex relationships between inputs and outputs
Decision Trees	Make decisions or classify data
Auto-Regressive Moving Average (ARMA)	Used for modeling and predicting future values in a time series
Fuzzy Logic	Represent and process uncertainty to make system complexity manageable
Rough Sets	Framework for the automated transformation of data into knowledge, rule induction, fault diagnosis, feature selection
Match Matrix	Enhanced ARMA model which uses historical data from different operations for prediction
Support Vector Machine (SVM)	Used to find an optimized separation hyperplane in the projected space to maximize the decision boundary
Hidden Markov Model (HMM)	Statistical model where the system being modeled is assumed to be a Markov process
Process and Product Monitoring and Control	Control chart theory uses rules to identify control bounds and trends