



U.S. DEPARTMENT OF
ENERGY

Nuclear Energy

Office Of Nuclear Energy Sensors and Instrumentation Annual Review Meeting

**Robust Online Monitoring Technology for Recalibration
Assessment of Transmitters and Instrumentation**

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Project Overview

- **Goal: Develop and evaluate a standardized framework for next-generation online monitoring applicable to current and future nuclear systems**

- **Participants:**
 - PNNL (Pradeep Ramuhalli, Ramakrishna Tipireddy, Megan Lerchen)
 - University of Tennessee Knoxville (Jamie Coble, Anjali Nair)
 - AMS (Brent Shumaker)

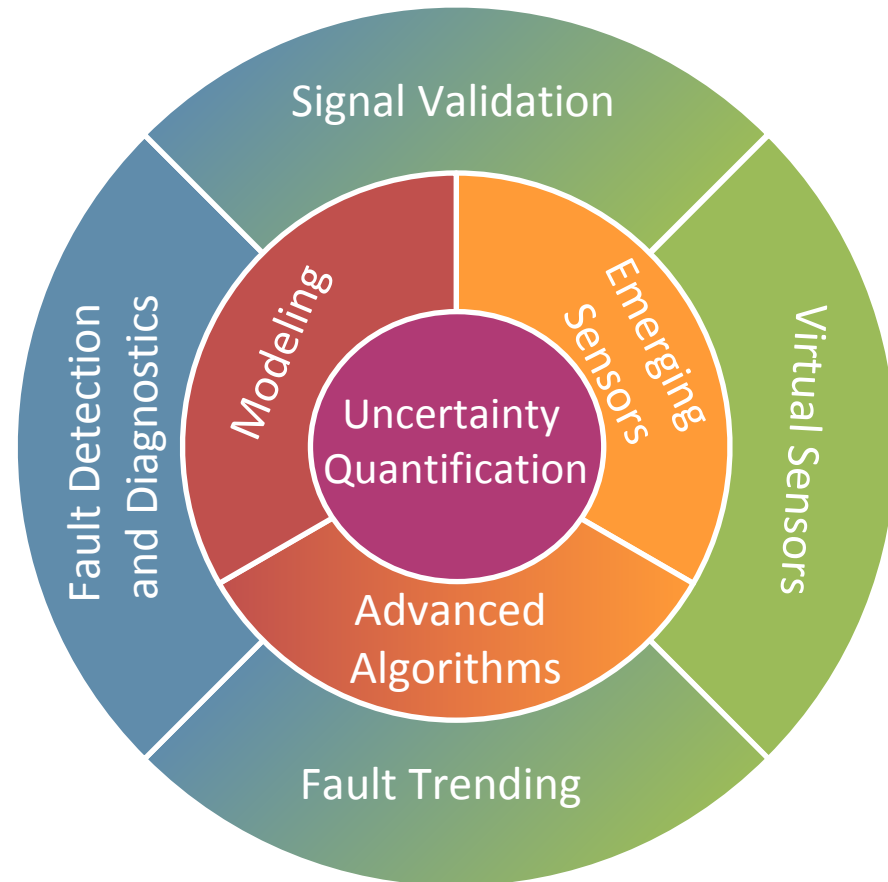
- **Schedule**
 - Three years (FY 2015 – FY 2017)



Objectives

■ Develop next-generation online monitoring applicable to current and future nuclear systems

- Apply data-driven UQ to develop methods for real-time calibration assessment and signal validation
- Robust virtual sensors to augment available plant information
- Technologies for sensor response-time monitoring
- Considerations for emerging sensor technologies





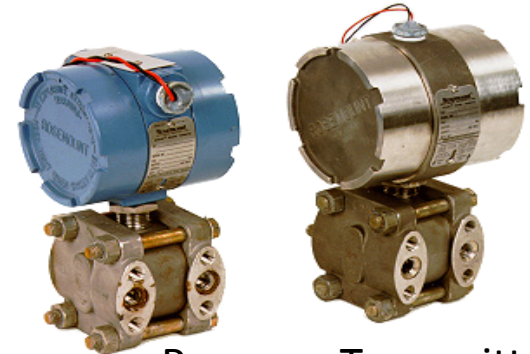
Project Background

- **Measurement reliability key to safe, economic and secure operation of nuclear systems**

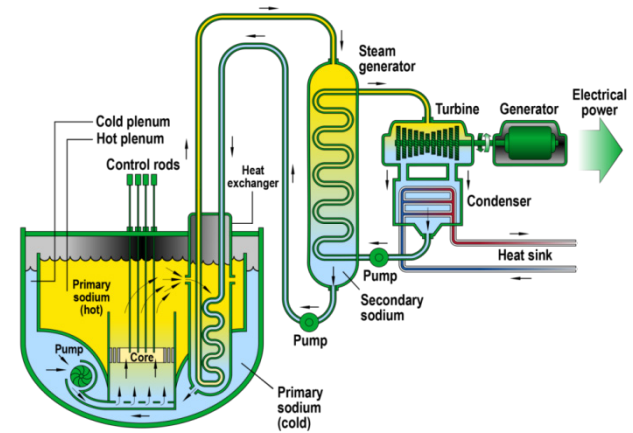
- Interval-based recalibration used to assure reliability

- **Current practices have several drawbacks**

- Time consuming and expensive
- Sensor calibration assessed infrequently
- Contributes to unnecessary radiological dose
- Unnecessary maintenance may damage healthy sensors
- Potential for limited opportunities for maintenance in future nuclear systems
- Different failure mechanisms for next-generation sensors and I&C



Pressure Transmitters





Sensor Performance Monitoring can Improve Reliability of Sensing

Online monitoring (OLM) supports condition-based calibration of key instrumentation

OLM technologies can

- Temporarily accommodate limited sensor failure
- Provide indications for measurements that cannot be made (virtual sensors)
- Ensure reliability of next-generation sensors and instrumentation through formal methods for uncertainty quantification
- Support extended sensor calibration cycles and reduce or eliminate TS-required periodic recalibration

The collage includes several key components:

- Top Left:** A screenshot of an "ON-LINE MONITORING" dashboard showing various sensor status indicators and data points.
- Top Right:** The cover of a technical report titled "On-Line Monitoring of Instrument Channel Performance" (TR-10496-R1 NRC-SER) from the NRC.
- Middle Left:** A GE Intelligent Platforms logo and a large image of a turbine.
- Middle Right:** An advertisement for "SignalPro" Anomaly Detection System, featuring the GE logo and the slogan "imagination at work".
- Bottom Left:** The cover of a "Technical Review of On-Line Monitoring Techniques for Performance Assessment" report, Volume 1: State-of-the-Art, published by the U.S. Nuclear Regulatory Commission.
- Bottom Right:** A screenshot of a software interface showing multiple data plots and graphs.

Technology Impact

■ Framework for next generation OLM that enables

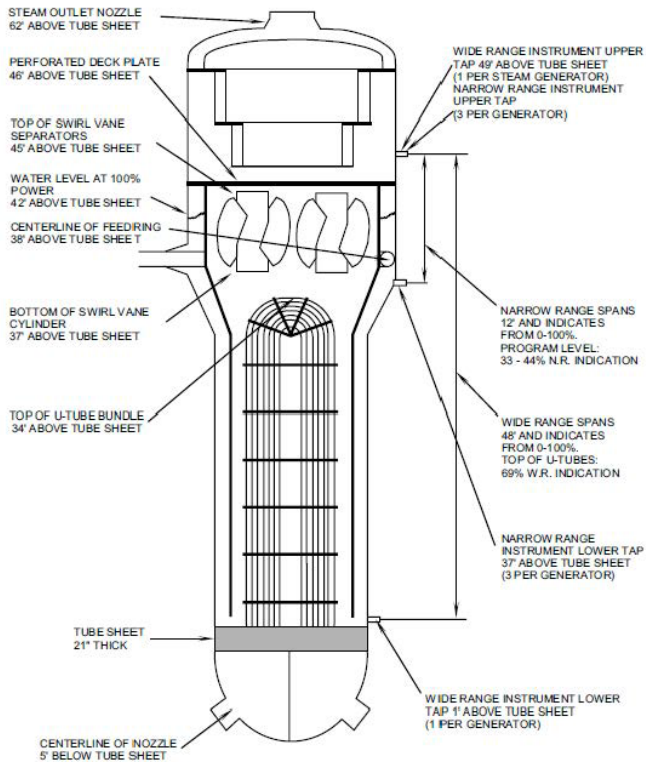
- Recalibration needs assessment for dynamic and steady-state operation
- Short-term operation with a limited number of failing sensors, through the use of virtual sensor technology
- Ability to derive plant information that currently cannot be measured using virtual sensors
- Monitoring and detection of degradation in sensor response time
- Predictive (over short-term) assessment of sensor failure
- OLM framework for emerging I&C technologies

■ Supports DOE-NE research objectives*

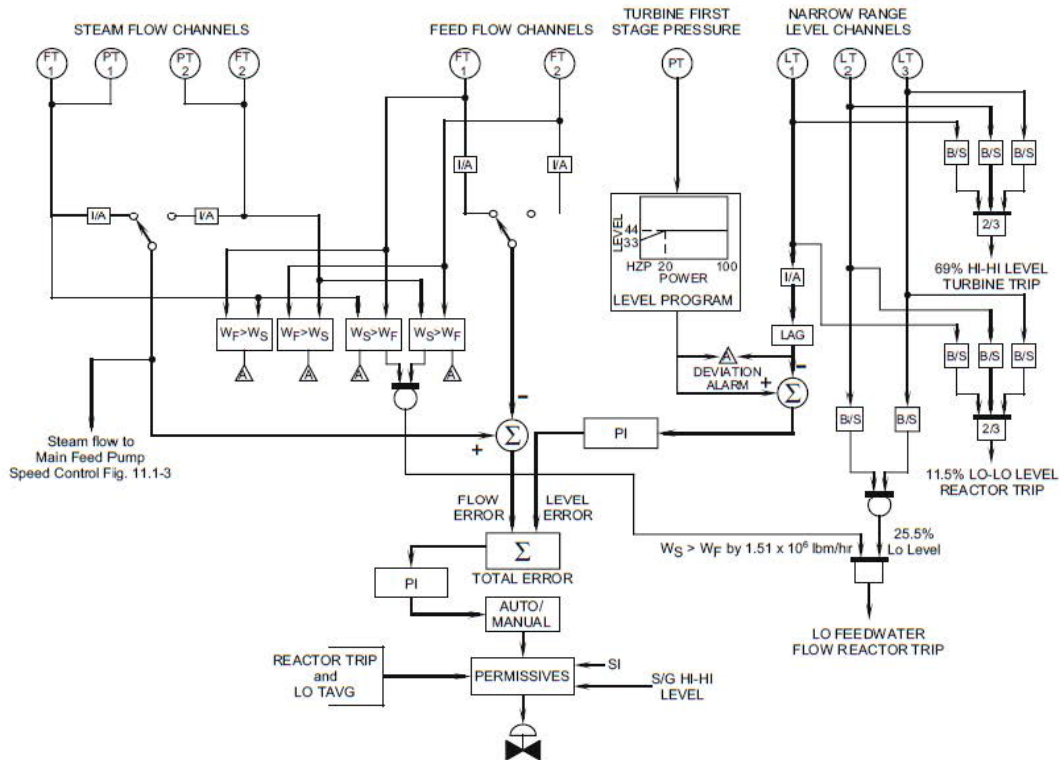
- Improve reliability, sustain safety and extend life of current reactors
- Improve affordability of new reactors



Example SG Level Measurement and Feed-water Control



NOTE: MEASUREMENTS ROUNDED TO THE NEAREST FOOT

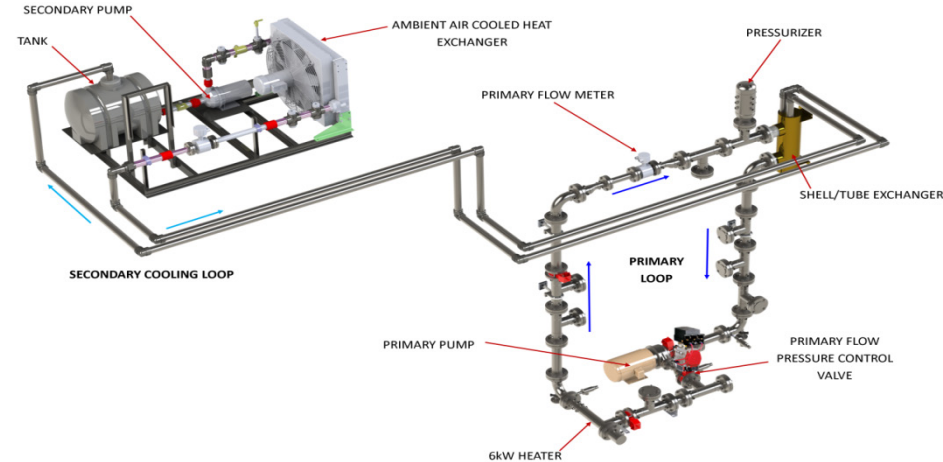


NRC ADAMS No. ML11223A293, Figures 11.1-1 and 11.1-4

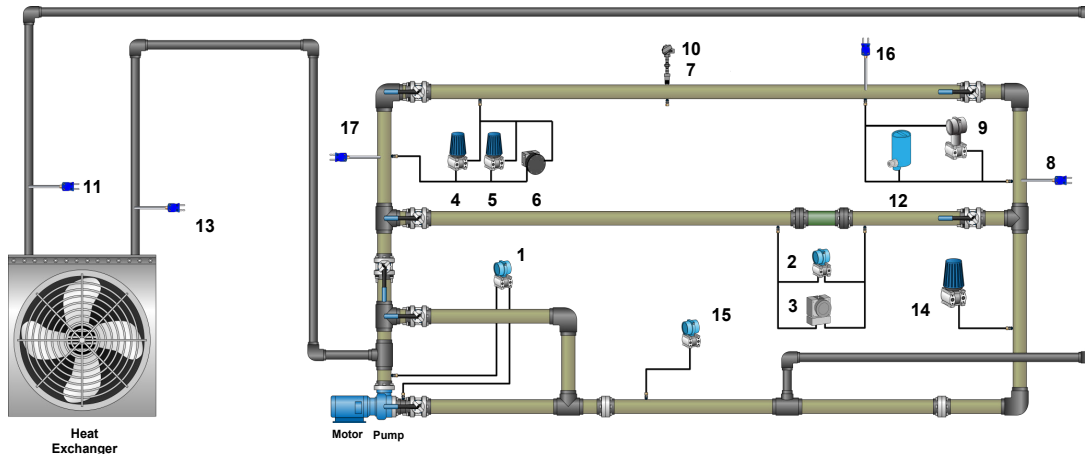


Testbeds Simulate Heat Exchanger Operations

- Simple heat exchanger loop
- Sensor and instrumentation models coupled to loop model
- Prescribed uncertainty levels to directly study effects on sensed values and OLM results
 - Normal and anomalous conditions



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ITEM	ID	SENSOR TYPE	MANUFACTURER
1	FT-4-1	DIFFERENTIAL PRESSURE	ROSEMOUNT
2	FT-3-1	DIFFERENTIAL PRESSURE (SMART)	ROSEMOUNT
3	FT-3-2	DIFFERENTIAL PRESSURE	BARTON
4	FT-1-1	DIFFERENTIAL PRESSURE	FOXBORO
5	FT-1-2	DIFFERENTIAL PRESSURE	FOXBORO
6	FT-1-4	DIFFERENTIAL PRESSURE (SMART)	BARTON
7	TE-1-2	RTD (SMART)	ROSEMOUNT
8	TC-2-1	THERMOCOUPLE TYPE-J (SMART)	ROSEMOUNT
9	FT-2-1	DIFFERENTIAL PRESSURE	SCHLUMBERGER
10	CTRL-TEMP	RTD (SMART)	ROSEMOUNT
11	TC-HX-OUT	THERMOCOUPLE TYPE-J	OMEGA
12	FT-2-3	DIFFERENTIAL PRESSURE	HONEYWELL
13	TC-HX-IN	THERMOCOUPLE TYPE-J	OMEGA
14	CTRL-PSR	GAUGE PRESSURE	FOXBORO
15	PT-2	GAUGE PRESSURE	ROSEMOUNT
16	TC-LOOP-FAR	THERMOCOUPLE TYPE-E	OMEGA
17	TC-PUMP-OUT	THERMOCOUPLE TYPE-K	OMEGA



Research Tasks

■ Signal validation and virtual sensors

- Evaluate how uncertainty drives minimum detection limits and acceptance criteria
- Estimate expected measurement values (and associated uncertainties) for replacing faulted sensors
- Evaluate the effect of using virtual sensors on OLM and OLM uncertainty
- Develop guidelines for condition-based sensor recalibration

■ Assess impacts of next generation sensors and instrumentation

- Requirements definition for OLM in next generation I&C
- Gaps assessment: Map algorithms (from other tasks) to requirements

■ Response time OLM

- Acceptance criteria development
- Adapt research in signal validation for response time OLM

■ Verification and validation based on data from a suitable test-bed or operating plant



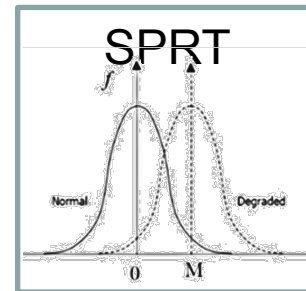
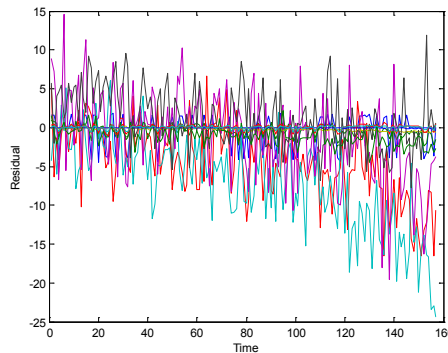
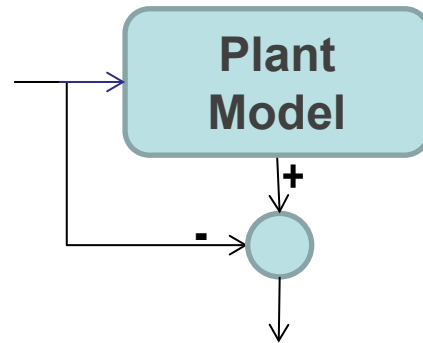
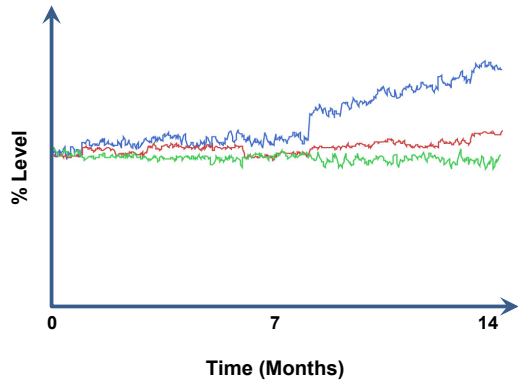
Online Monitoring Overview

■ Non-intrusive

- Plant data collected during operation

■ Anomalies due to sensor fault vs. process change

■ Acceptance criteria define normal performance bounds



Process Fault?
Sensor Fault?

Gaussian Processes

■ Use Bayesian statistics to develop models and quantify uncertainty

- Combine what we already know (Prior) and the model discrepancy with the data (Likelihood).

■ General model:

$$Y = \beta(x) = \mu(x) + w(x) + \varepsilon(x)$$

■ General approach:

- Assume prior for $\beta(x)$
- Conditional prior distributions on parameters defining correlation functions represented through a basis expansion
 - Likelihood information using multi-output Gaussian processes that explicitly treat correlations between distinct output variables as well as space and/or time.
- Bayesian inference (using a training data set) performed to extract posterior distributions
- Update model in the light of new observations



High Confidence Signal Validation Through GP Modeling of Monitoring System Residuals

- Monitoring system residual is modeled as the combination of stationary (nominal) and dynamic (faulted) components

$$r(z_i, \omega_i) = \underbrace{y(z_i, \omega_i)}_1 - \underbrace{z_i}_2 = \underbrace{\delta(z_i, \omega_i) + e_i}_3 + \underbrace{\rho\eta(\Delta t_i, l_i)}_4$$

- $y(z_i, \omega_i)$ **(1)** is the monitoring system prediction at point z_i , given model parameters ω_i
- z_i **(2)** is the measurement from the system
- The stationary component of the monitoring system residual is a combination of model inadequacy, $\delta(z_i, \omega_i)$, and measurement noise, e_i **(3)**
- Anomalies manifest as dynamic component of residual, $\rho \cdot \eta(\Delta t_i, l_i)$ **(4)**, where Δt_i is the elapsed time from onset of fault, η is a function relevant to the type of fault with parameters l_i , and ρ is a constant between 0 and 1 related to the model sensitivity



Implementation Status of Signal Validation

■ Initially focused on implementing the stationary component GP model

- Implementation is ongoing with testing using a variety of available data from small flow loops and reactor coolant loops

■ Assumptions:

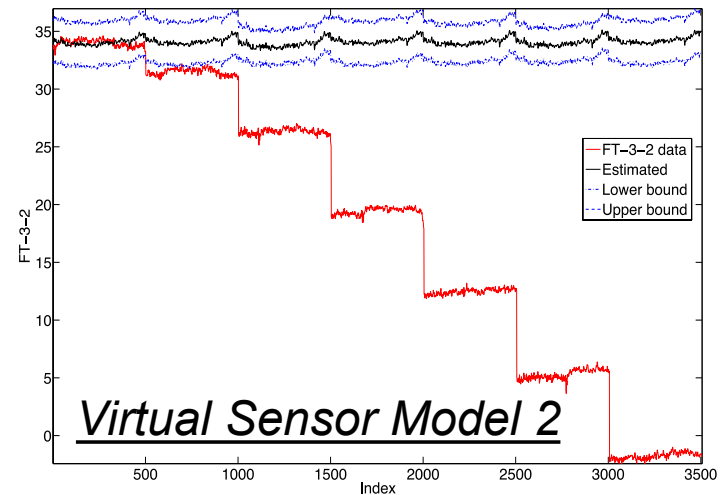
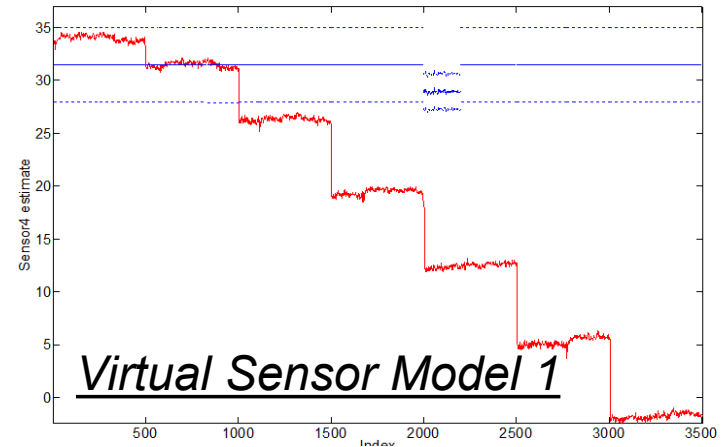
- Measurements, z , follow a non-stationary Gaussian distribution
- Monitoring system model, $y(z, \omega)$, is static and pre-defined
 - Auto-associative kernel regression is current focus
 - Framework is model agnostic
- Healthy sensor residuals are stationary in time and across the sensor range



Virtual Sensing

■ Virtual sensor model using Gaussian Process

- Sensor drift: Data with one faulty sensor
- Model inputs include control and process sensor measurements
- Predicted sensor value includes uncertainty in prediction
- Results indicate potential for predicting sensor data with uncertainty bounds, for sensor with drift
- Uncertainty bounds for the predicted sensor values are dependent on richness of data used for generating the model – approaches, including collecting additional data, to tighten bounds being examined





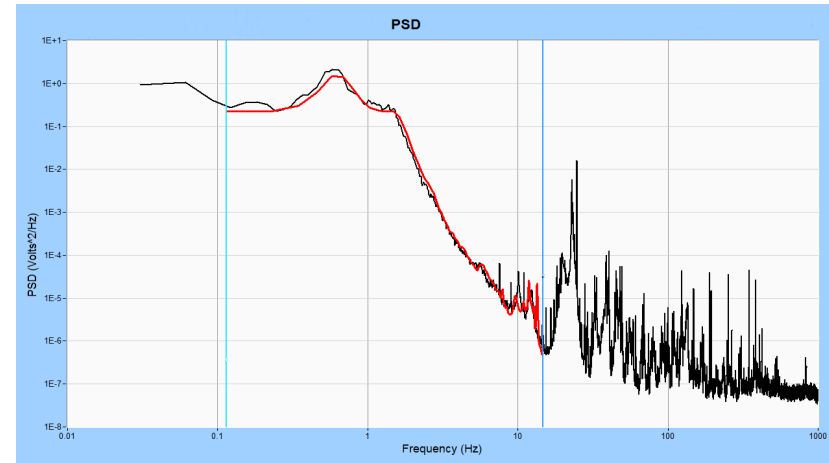
Sensor Response OLM

■ Automated Sensor Response OLM

- Dynamic response is a key indicator of sensor system performance and health
- Traditional noise analysis methodology relies on knowledge from experienced engineers
- Expert knowledge will be combined with automated analysis tools to provide accurate and repeatable sensor response results that can be integrated with other OLM analysis techniques

■ Noise Testing and Algorithm Development

- Acquire high-frequency noise data on nuclear-grade transmitters in the test loop
- Simulate voids, leakages, and sensing line blockages to facilitate the development of robust sensor response evaluation and diagnostic algorithms



Accomplishments

-
- Implemented and evaluated initial approach to virtual sensing
 - Identified needs for sensor response time OLM
 - Implemented initial algorithm for signal validation based on Gaussian Process models for monitoring system residuals
 - Update on signal validation and virtual sensing algorithm development (PNNL-24702)

 - **Journal/Conference papers and presentations**
 - Coble, JB and A Nair, "High-Confidence Signal Validation for Online Sensor Calibration Assessment," Presented at *MFPT 2015*. Huntsville,AL: May 12-14, 2015.
 - Nair, A, and JB Coble, "A High Confidence Signal Validation Technique for Sensor Calibration Assessment in Nuclear Power Systems." 2015 ANS Winter Meeting and Nuclear Technology Expo. Washington, DC: November 8-12, 2015.



Next Steps

■ Signal validation

- Complete implementation and testing of sensor status and fault diagnostics using data-driven UQ
- Input to advanced monitoring/control algorithms

■ Virtual sensing

- Alternate algorithms for virtual sensing
- Uncertainty must account for spillover of faulty reading into estimate
- Number of allowed virtual sensors, and duration of applicability to be determined

■ Response time OLM

- Implement and verify algorithms for noise analysis

■ OLM requirements using emerging I&C technologies

■ Verification and validation of algorithms using data from test-beds as well as data from operating plants

Conclusion

- **Research focused on addressing high-impact technical gaps to developing a standardized framework for robust next-generation online monitoring**
- **Outcomes enable**
 - Extended calibration intervals and relief of even limited periodic assessment requirements
 - Assessment of sensor measurement accuracy with high confidence
 - Derived values for desired parameters that cannot be directly measured
- **Outcomes support**
 - Improved reliability and economics for current and future nuclear systems
 - Deployment of advanced sensors (ultrasonic, fiber optic, etc.) and instrumentation (digital I&C, wireless, etc.)