



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

**Pradeep Ramuhalli,
Ramakrishna Tipireddy,
Megan Lerchen**

**Pacific Northwest National
Laboratory**

**Jamie Coble,
Anjali Nair,
Samuel Boring**

**University of
Tennessee
Knoxville**

**Brent Shumaker,
Hash Hashemian**

**Analysis and
Measurement Services**

October 12-13, 2016

Project Overview

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

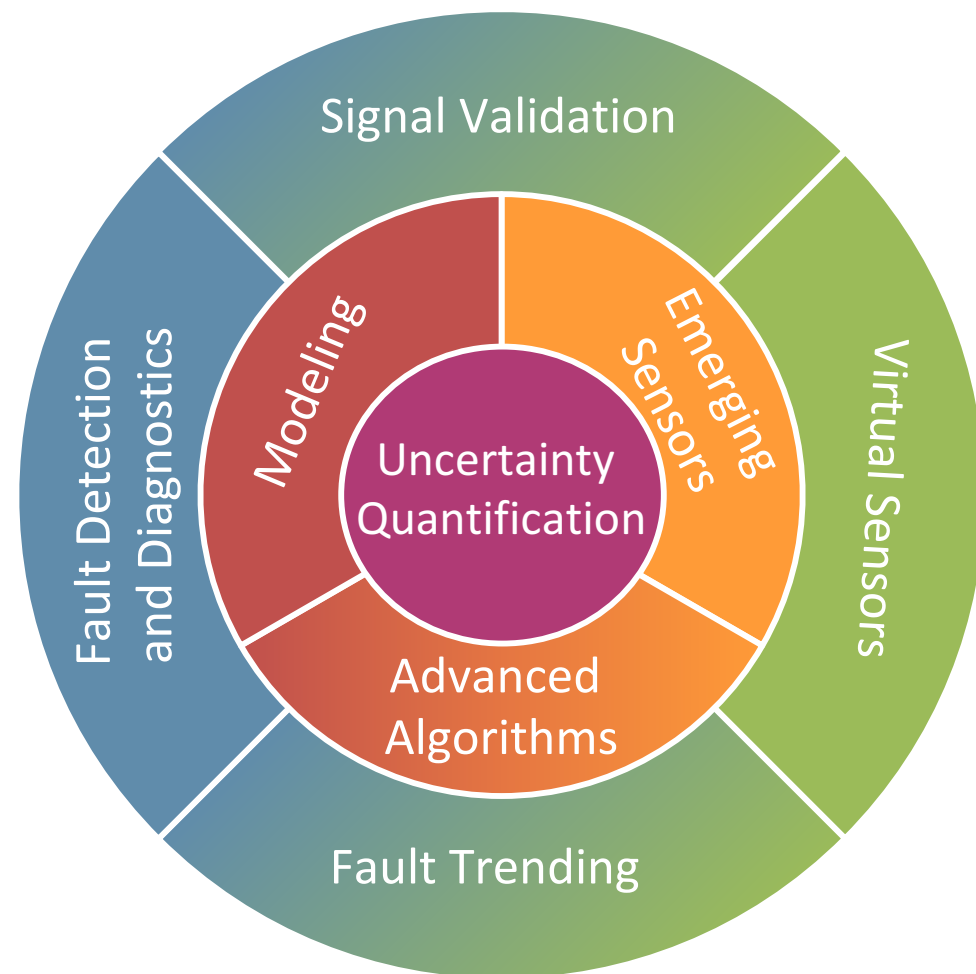
- **Participants:**
 - PNNL (Pradeep Ramuhalli, Ramakrishna Tipireddy, Megan Lerchen)
 - University of Tennessee Knoxville (Jamie Coble, Anjali Nair, Sam Boring)
 - AMS (Brent Shumaker)

- **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 automated sensor response-time monitoring
- Considerations for emerging I&C technologies





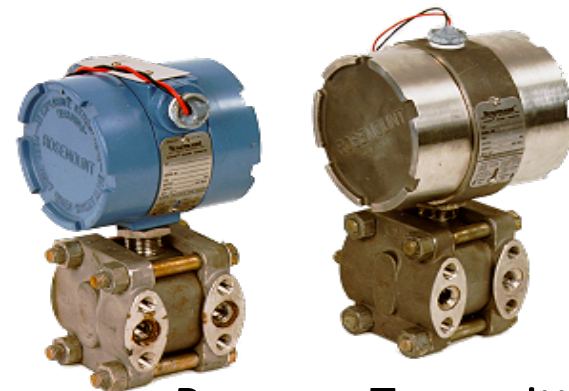
Project Background

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

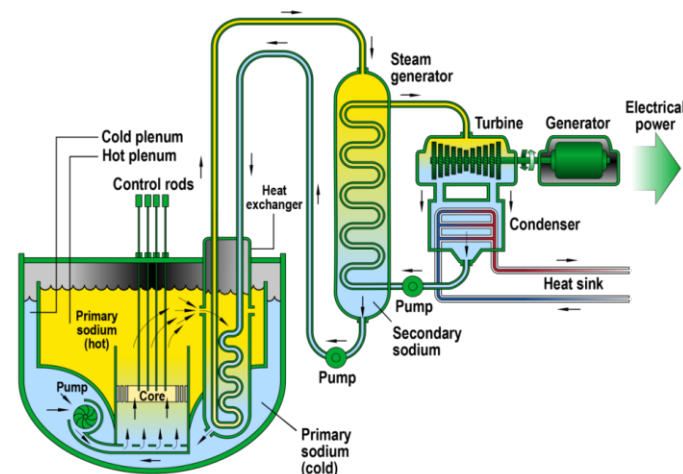
- Interval-based recalibration used to assure reliability

■ 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

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

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

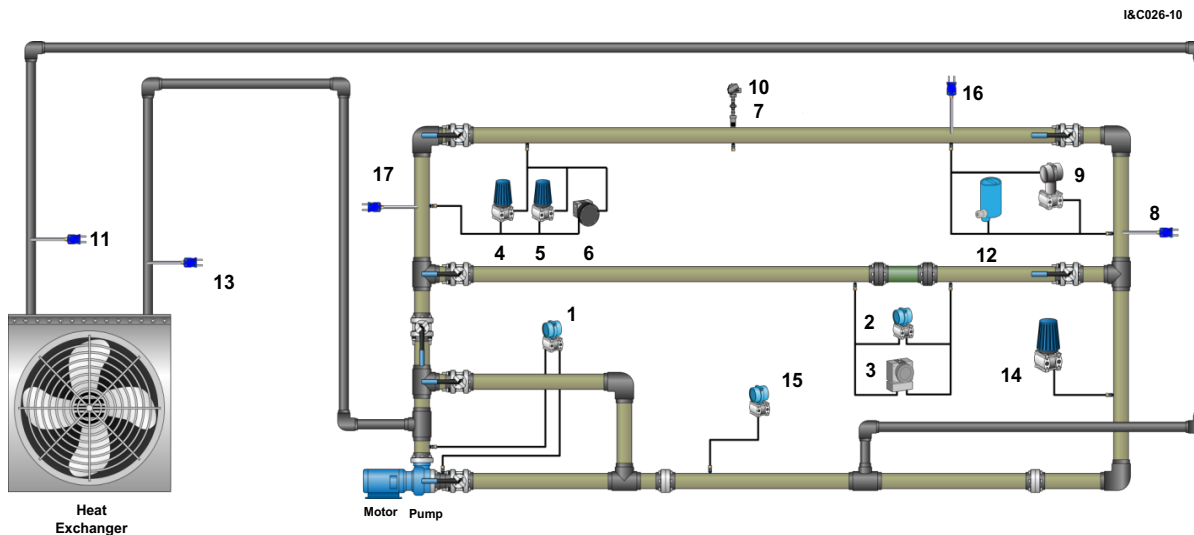
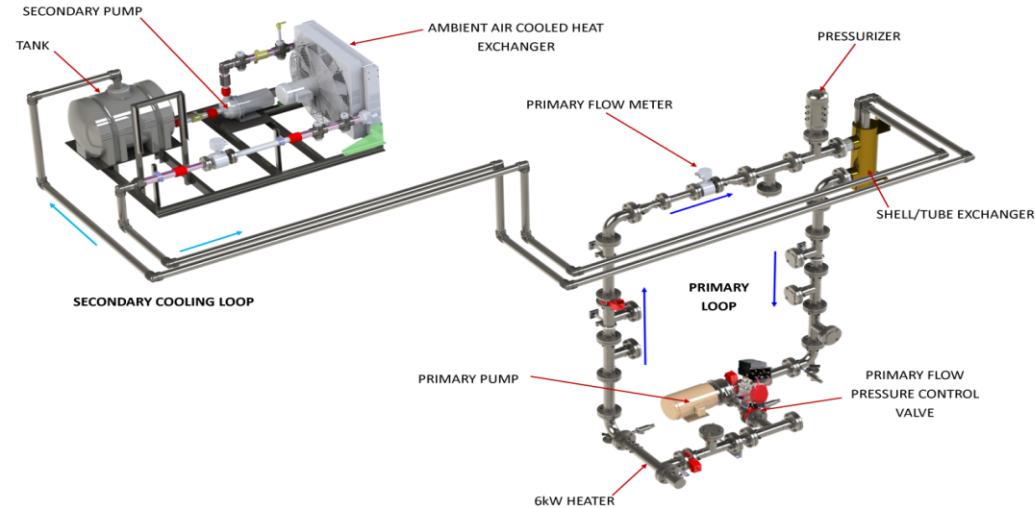
- Acceptance criteria development
- Adapt research in signal validation for response time OLM

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



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

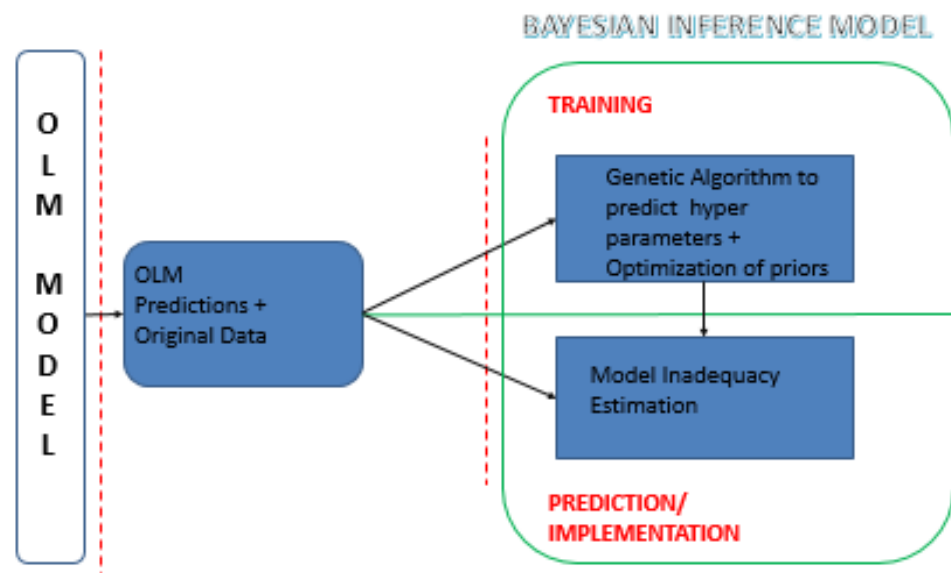


I&C026-10

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

Signal Validation using Bayesian Inference Model

- **Uncertainty quantification of OLM residuals**
- **Focus on differentiability of errors of interest, such as model inadequacy and instrument errors**
 - Model inadequacy is assumed stationary across time and operating conditions
- **Bayesian inference and Gaussian process models applied for predicting model inadequacy values**
- **Model trained and tested using Nuclear coolant data and the flow loop data collected by AMS**
 - Normal and anomalous conditions





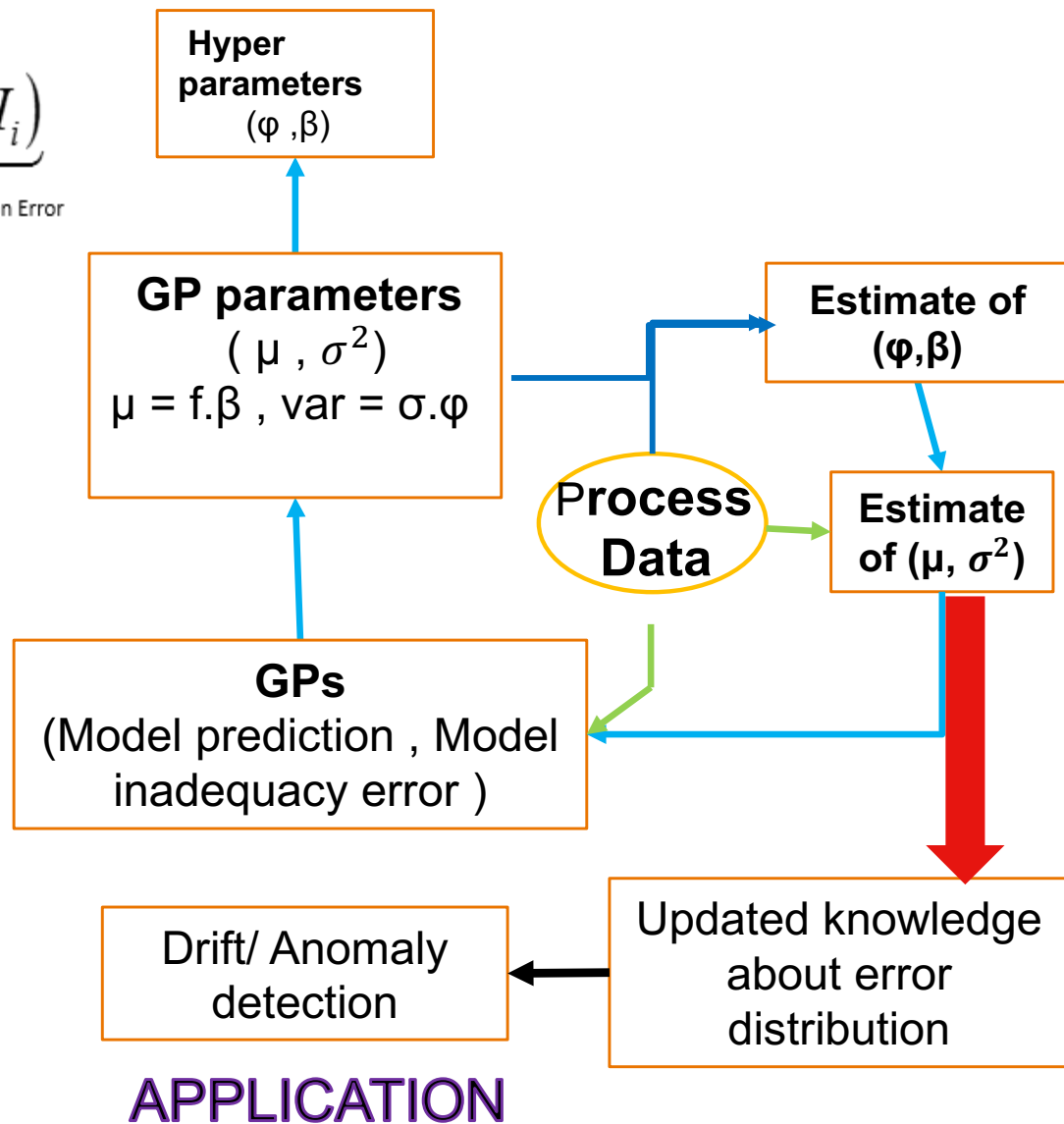
Model process overview

$$r(z_i, \omega_i) = \underbrace{y(z_i, \omega_i)}_{\text{Predictive Model}} - \underbrace{z_i}_{\text{Observation / Data}} = \underbrace{\delta(z_i, \omega_i)}_{\text{Model Inadequacy}} + \underbrace{e_i}_{\text{Observational Error}} + \underbrace{\rho \eta(\Delta t_i, I_i)}_{\text{Sensor Degradation Error}}$$

GP 1 **GP 2**

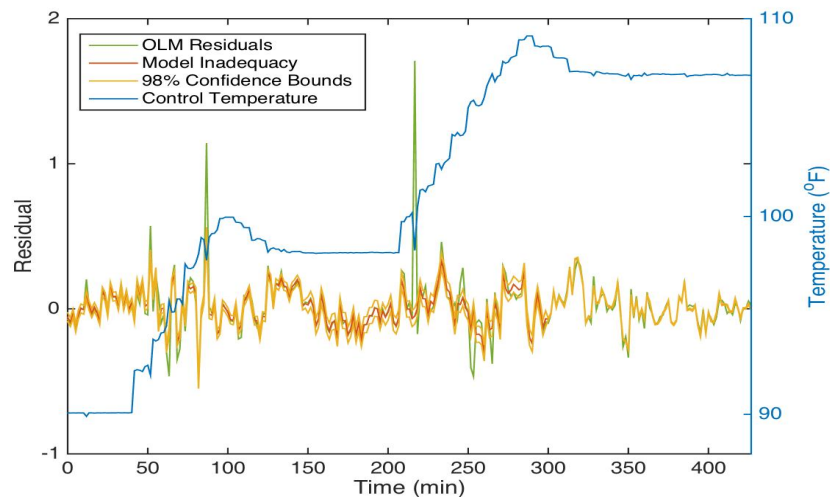
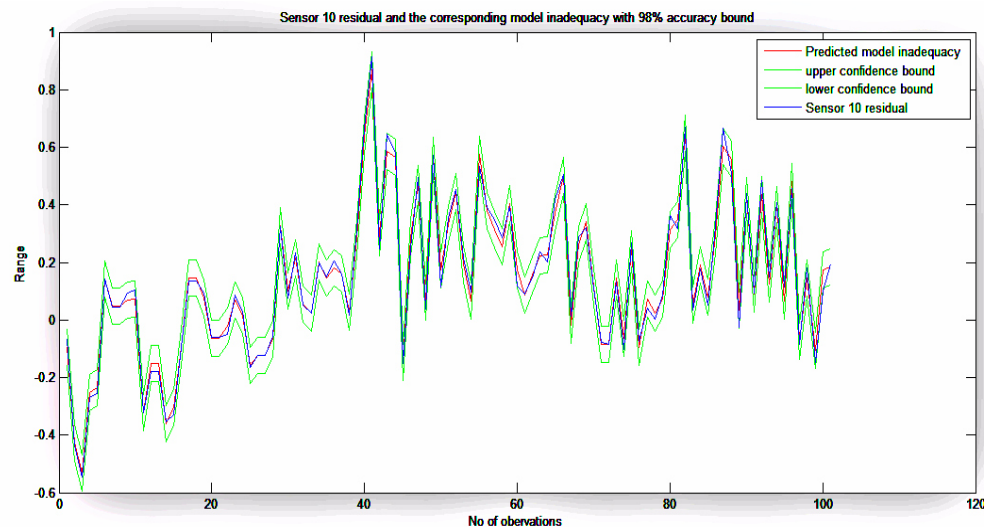
On the basis of the defined priors in the form of GP1 and GP2 , the Bayesian inference model is implemented

The distribution of interest : the model inadequacy is updated using data and various parameter estimates. This is used to bound the error and uncertainty of the prediction





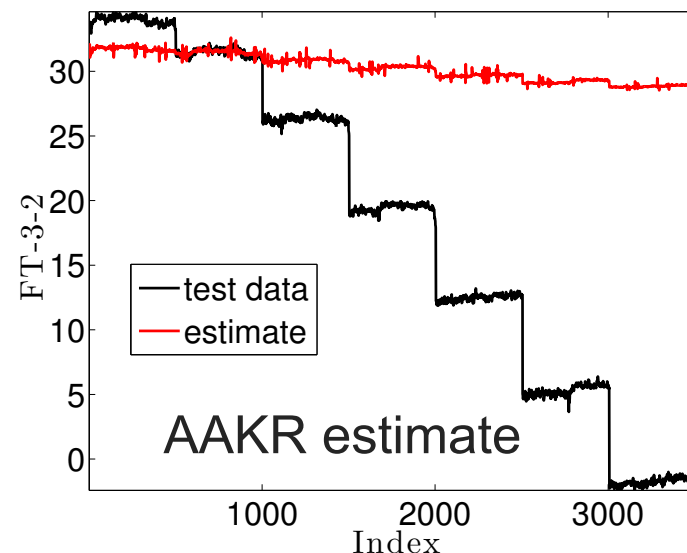
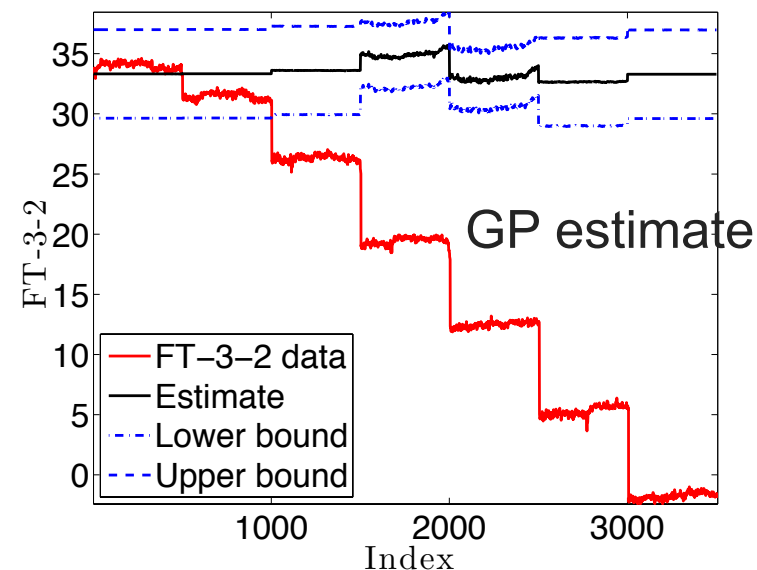
- **Current model inadequacy predictions meets the model assumptions under normal steady state and transient conditions**
- **Evaluating performance under faulted conditions**
 - Current system performance is not sufficiently robust to faults
- **Future work will integrate with forced flow loop data and models at UTK**



Virtual Sensing

■ Data-driven virtual sensor models

- Models used for fault detection are often applicable for virtual sensing
 - Each model has pros and cons relative to virtual sensing
- Models sensitive to training data used to derive parameters
 - Data sets must include fault data to allow for robust prediction by some models
- Alternative independent variables may enable more robust estimates at the expense of robust fault detection
 - Currently being evaluated



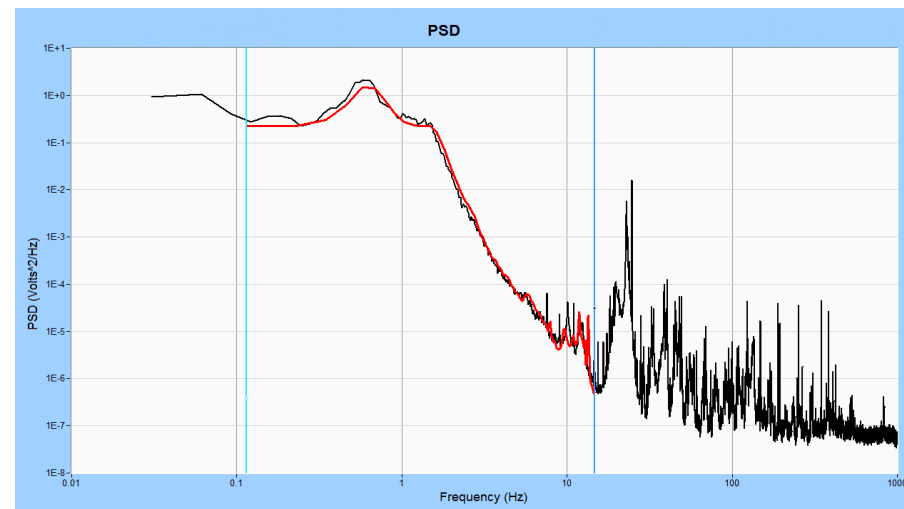
Sensor Response OLM

■ 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

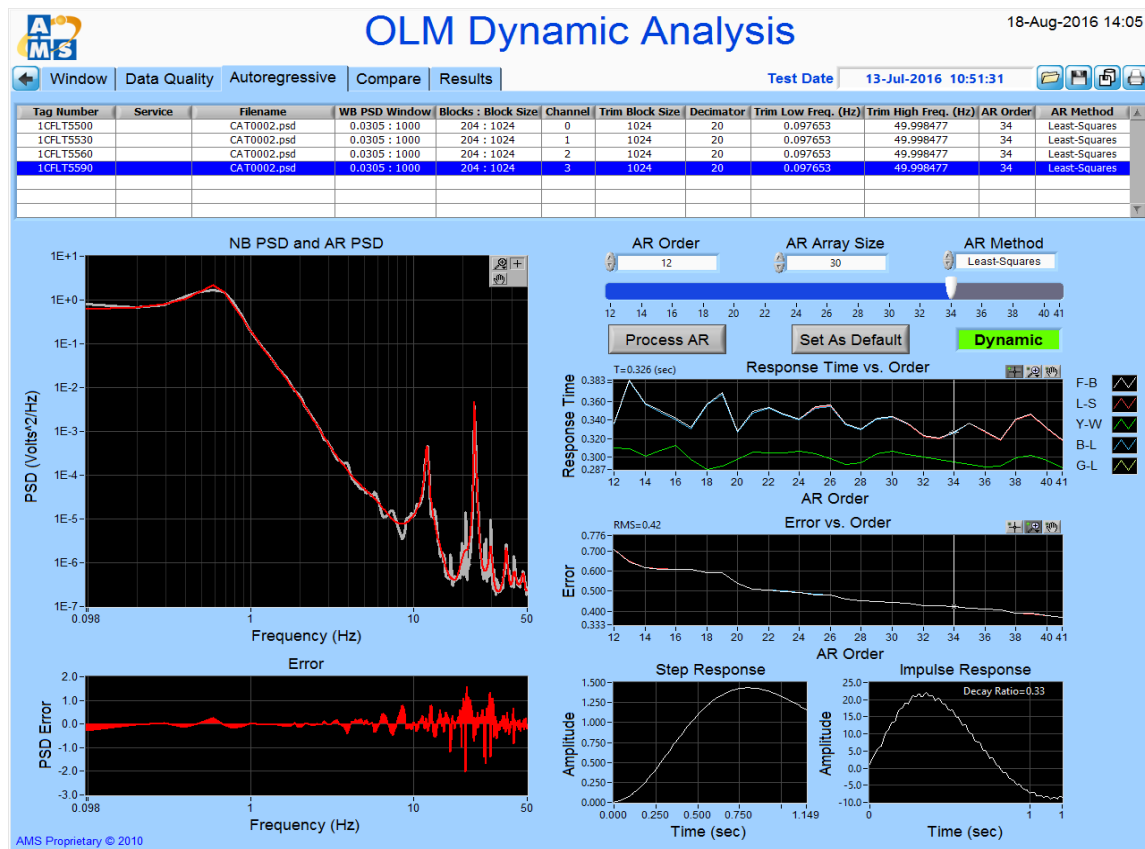
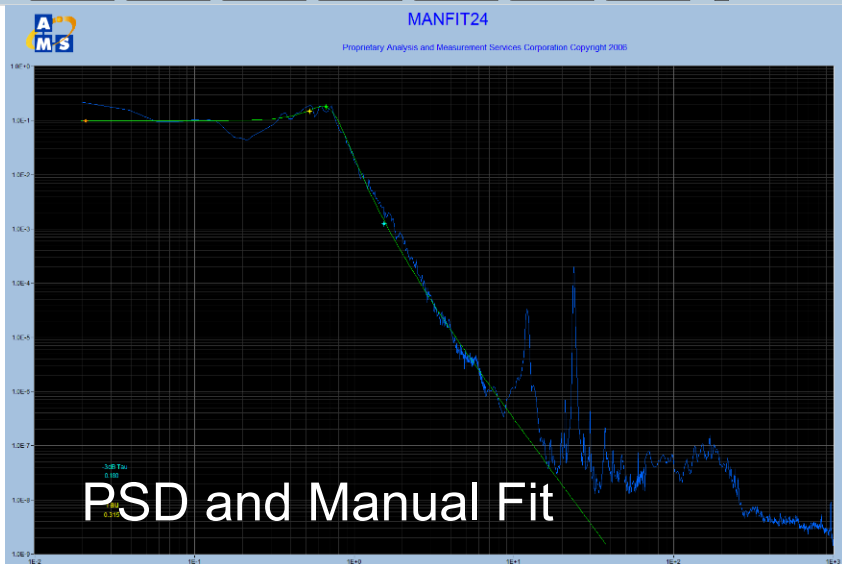
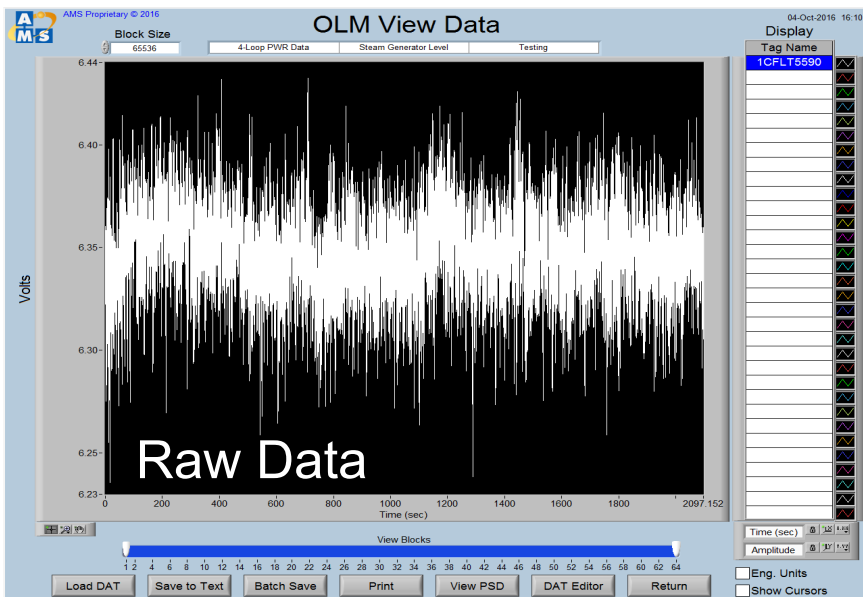


Noise Analysis for Actual Plant Data

- Data recorded from 4 protection sets, 44 sensors
- 35 minutes of data per protection set, 2000 S/sec
- RCS Flow and SG Level – 28 transmitters
- Pressurizer Pressure and Steam Pressure – 16 transmitters
- Noise data converted to spectrums
- Data and spectrums analyzed using existing methods
- AR models created and evaluated
- Results compared



Example of Steam Generator Level Data



Automated Model Fitting and Analysis



Nuclear Energy

Item #	Service	Tag	Auto AR (sec)	Manual (sec)	ΔT (sec)
1	RCS Flow	RCFT-001	0.27	0.29	-0.02
2		RCFT-002	0.31	0.31	0.00
3		RCFT-003	0.30	0.28	0.02
4		RCFT-004	0.36	0.34	0.02
5		RCFT-005	0.28	0.27	0.01
6		RCFT-006	0.29	0.28	0.01
7		RCFT-007	0.22	0.23	-0.01
8		RCFT-008	0.26	0.26	0.00
9		RCFT-009	0.24	0.22	0.02
10		RCFT-010	0.23	0.2	0.03
11		RCFT-011	0.24	0.2	0.04
12		RCFT-012	0.26	0.25	0.01
13	SG Level	SGLT-001	0.57	0.62	-0.05
14		SGLT-002	0.41	0.41	0.00
15		SGLT-003	0.39	0.37	0.02
16		SGLT-004	0.35	0.36	-0.01
17		SGLT-005	0.42	0.43	-0.01
18		SGLT-006	0.34	0.33	0.01
19		SGLT-007	0.34	0.3	0.04
20		SGLT-008	0.38	0.33	0.05
21		SGLT-009	0.41	0.39	0.02
22		SGLT-010	0.37	0.39	-0.02
23		SGLT-011	0.44	0.42	0.02
24		SGLT-012	0.41	0.41	0.00
25		SGLT-013	0.34	0.33	0.01
26		SGLT-014	0.34	0.33	0.01
27		SGLT-015	0.42	0.42	0.00
28		SGLT-016	0.38	0.35	0.03

DP Transmitters

Item #	Service	Tag	Auto AR (sec)	Manual (sec)	ΔT (sec)
1	PZR Pressure	PZPT-001	0.37	0.38	-0.01
2		PZPT-002	0.54	0.55	-0.01
3		PZPT-003	0.40	0.43	-0.03
4		PZPT-004	0.44	0.44	0.00
5	Steam Pressure	MSPT-001	0.06	0.07	-0.01
6		MSPT-002	0.07	0.08	-0.01
7		MSPT-003	0.06	0.08	-0.02
8		MSPT-004	0.07	0.07	0.00
9		MSPT-005	0.06	0.08	-0.02
10		MSPT-006	0.03	0.04	-0.01
11		MSPT-007	0.10	0.08	0.02
12		MSPT-008	0.13	0.11	0.02
13		MSPT-009	0.08	0.08	0.00
14		MSPT-010	0.08	0.08	0.00
15		MSPT-011	0.09	0.09	0.00
16		MSPT-012	0.07	0.07	0.00

Pressure Transmitters

Accomplishments

- **Implemented and evaluated initial approaches under each task**
 - Signal validation, virtual sensing, response time monitoring
- **Integration activities begun**
- **Updates on research status in FY16 (PNNL-25382 , PNNL-25104, PNNL-24702)**
- **Journal/Conference papers and presentations**
 - Nair, A, and JB Coble, "A High Confidence Signal Validation Technique for Sensor Calibration Assessment in Nuclear Power Systems." 2015 ANS Winter Meeting and Technology Expo. November 7-12, 2015: Washington, DC.
 - Nair, A, S Boring, JB Coble, "High Accuracy Signal Validation Framework for Sensor Calibration Assessment in NPPs." 2016 ANS Winter Meeting and Technology Expo. November 6-10, 2016: Las Vegas, NV.
 - Nair, Anjali Muraleedharan, "Bayesian Framework for High Confidence Signal Validation for Online Monitoring Systems in Nuclear Power Plants. " Master's Thesis, University of Tennessee, 2016. http://trace.tennessee.edu/utk_gradthes/4060
 - Tipireddy R, ME Lerchen, and P Ramuhalli. 2016. "Virtual sensors for robust on-line monitoring (OLM) and Diagnostics." Submitted to International Conference on Prognostics and Health Management (IEEE PHM2016).
 - Tipireddy R, ME Lerchen, and P Ramuhalli. 2016. "Methodologies for Virtual Sensing in nuclear plant on-line monitoring." In preparation, for submission to IEEE Trans. Rel.

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.)