# Robust Online Monitoring Technologies for Nuclear Power Plant Sensors

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## INTRODUCTION

Robust online monitoring (OLM) technologies are expected to enable the extension or elimination of periodic sensor calibration intervals in operating and new reactors. Specifically, the next generation of OLM technology is expected to include newly developed advanced algorithms that improve monitoring of sensor/system performance during reactor operation. These advances in OLM technologies will improve the safety and reliability of current and planned nuclear power systems through improved accuracy and increased reliability of sensors used to monitor key parameters. This paper summarizes the work performed by the authors for the development and demonstration of advanced OLM algorithms for 1) calibration monitoring, 2) virtual sensing, and 3) automated response-time assessment of nuclear power plant sensors. Integration of signal validation, virtual sensing, and response time assessment are critical to achieving a deployable robust OLM technique that can be used by nuclear power plants (NPPs) to extend or eliminate periodic sensor calibration intervals, verify the health of critical instrumentation, and enable the use of plant data to derive information that currently cannot be measured.

## CALIBRATION MONITORING

The current industry practice for calibrating pressure, level, and flow sensors in NPPs is highly intrusive, expensive, and inefficient [1]. This process, carried out every 18–24 months, requires the removal, recalibration, and reinstallation of every sensor and associated channels as specified in the Technical Specification and regulated by the NRC [2]. This method involves testing of instrumentation in an isolated environment, followed by appropriate recalibration to ensure its functionality over the next cycle. The recalibration process is time, economic, and labor intensive. The average cost of calibrating a single sensor is between \$3000–\$6000, with about 50–150 sensors needing recalibration during any given cycle [3]. This recalibration process can also introduce errors in previously healthy sensors. Furthermore, this periodic approach may not be appropriate or sufficient in future reactors with longer operating cycles, harsher environments, and new sensor types.

The technical and economic inefficiencies of the current sensor calibration approach can be overcome using OLM. OLM evaluates existing sensor measurements (typically stored in the plant computer) that are taken while the plant is operating to verify the health of the sensors or detect anomalies in plant processes. For calibration monitoring, OLM data can be used to determine which sensors are providing erroneous measurements, so that recalibration is performed only on sensors that exhibit calibration issues [4]. Hence, calibration monitoring with OLM presents the possibility of extending and eventually eliminating scheduled periodic recalibration activities over multiple reactor cycles.

## VIRTUAL SENSING

A virtual sensor is a software tool that receives measured data as an input from the available physical sensors and predicts the process output corresponding to a sensor whose measurement is either not available or corrupted. If sensor drift or other problems are detected using OLM, immediate action to repair or replace the faulty sensor may not always be feasible. In such cases, the use of a virtual sensor to estimate the correct measurement from the faulty sensor *as if it were healthy*, for a short duration, may provide a feasible alternative to immediate maintenance action. Virtual sensors may also be used in cases where process data that is needed cannot be currently measured. This may be because of a lack of instrumentation at the location where the measurement is desired or if a reliable measurement of the process parameter does not currently exist. Examples of the latter are a need to measure neutron flux in-core at startup, and the desire to monitor core support structure integrity in advanced reactors. In these cases, OLM algorithms can be used to infer the desired measurement from the analysis of existing sensors that are related to the desired measurement.

## RESPONSE TIME

Pressure, level, and flow transmitters in NPPs must respond to changes in the processes that they are measuring in a prescribed amount of time in order ensure the plant safety systems actuate properly in accident conditions. As such, the response time of NPP sensors is an important characteristic of sensor health that must be verified. For pressure transmitters, response time testing has been traditionally performed using the hydraulic ramp testing method or by noise analysis, which analyzes changes in the spectral characteristics of sensor measurements taken at high data acquisition rates. The noise analysis technique has proven to be an effective alternative to the traditional time-intensive hydraulic ramp testing method; however, the analysis of noise data is labor intensive and relies on expert analysis. Research described in this paper summarizes the authors' work in automating noise analysis so that the response time of NPP sensors can be determined using advanced OLM algorithms.

## OLM ALGORITHMS

OLM techniques typically use an empirical plant model, where the model parameters are derived from a known data set containing examples of measurements from normal and transient conditions. Kernel regression methods are commonly used as the plant model and model residuals (the difference between the model prediction and the measurement) are analyzed to detect anomalies [5]. These techniques are generally applied to assess sensor calibration from the measured signal magnitude with limited consideration of sensor response time. Response time analysis, on the other hand, generally relies on an assessment of spectral information derived from sensor measurements. In the research summarized in this paper, the authors incorporated several OLM techniques to perform calibration monitoring, virtual sensing, and response time estimation including Auto-Associative Kernel Regression (AAKR), Gaussian Process Latent Variable Models (GPLVMs), and Auto-Regressive (AR) modeling. Details regarding these algorithms can be found in [6].

## DATA SOURCES

To verify and validate the OLM algorithms used in this research, the authors collected data from laboratory test loops at AMS Corporation and the University of Tennessee, and used existing sensor data from operating NPPs. A diagram of one of the laboratory test loops used to produce OLM data for this research is shown in Fig. 1.

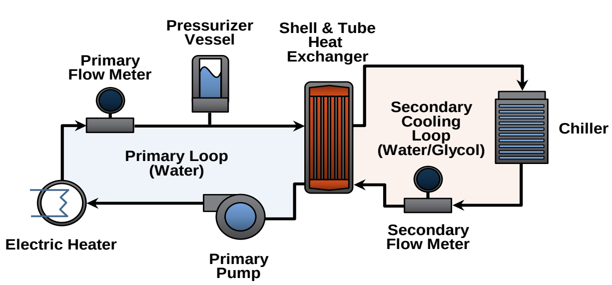


Fig. 1. Simplified flow loop piping and instrumentation diagram.

The flow loop shown in Fig. 1 is a light water test platform in the laboratories of AMS Corporation that is designed to simulate steady-state and transient fluid system conditions under forced flow and natural circulation conditions. This loop allows researchers to independently vary process conditions such as flow rate, temperature, and pressure across a relatively wide range of operating conditions. The flow loop is composed of two major sub-systems: 1) the primary water loop where most of the research tasks are focused and 2) the secondary cooling loop, which serves to provide a constant temperature heat sink for the primary loop. The primary loop has over 200 instrumentation ports and serves as a source of OLM data for both signal validation and response time testing. The primary loop is a closed system capable of being pressurized up to 1.03 MPaG while the secondary loop is atmospheric.

## RESULTS

To verify and validate the algorithms for sensor fault detection and virtual sensing, the authors used data from the laboratory flow loops and created fault conditions either by simulating drift or physically drifting the loop transmitters while the loop was operating. The purpose of these experiments was to identify the strengths and limitations of the OLM algorithms for robust monitoring. For simplicity, only three examples are described in this paper. More detailed results are provided in [6].

### Example 1

Fig. 2 shows the AAKR model residuals of three flow sensors (PMAG, SMAG, and Cor) and one temperature sensor (PRTD4). For this dataset, simulated drift was applied to the data of the PMAG sensor, while the data for the remaining sensors was not drifted. As shown in Fig. 2, the drift of the PMAG sensor affects the residuals of the other two flow sensors (SMAG, Cor) while the temperature sensor residuals (PRTD4) are largely unaffected. In this case, the OLM algorithm correctly identifies the faulted sensor (PMAG), but also indicates issues in the undrifted flow sensors (SMAG, Cor).

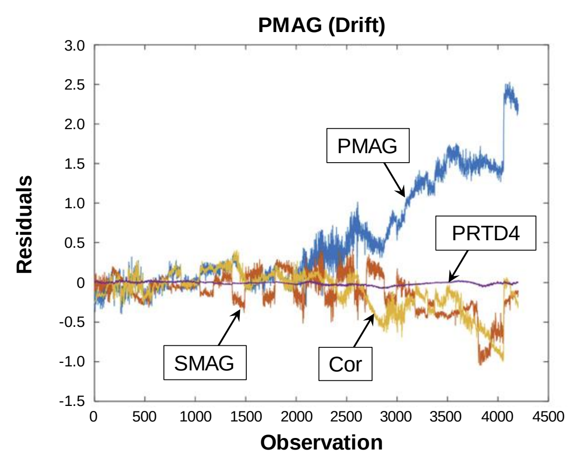


Fig. 2. Example 1 AAKR residuals.

**Example 2**

Fig. 3 shows the results of a GPLVM model when tested with a similar dataset as used in Example 1. In this case, the model output remains steady while the actual sensor is drifted. This experiment indicated that the GPLVM algorithm shows robustness to the drifting of one of the sensors in the model, and may be more suited to providing virtual sensors than AAKR algorithms.

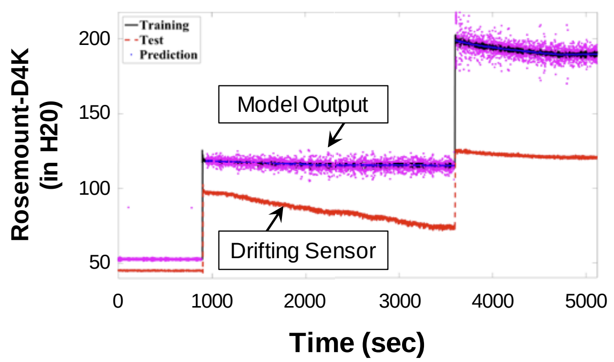


Fig. 3. GPLVM model results for drifting sensor.

**Example 3**

For automated response time algorithm validation, AR models were created using data from actual operating NPPs over several years, and the automated response-time results were compared to the results obtained from the more manually intensive manual noise results. As shown in the example results in TABLE I, the automated response time results were comparable to the manual noise analysis results.

As detailed in [6], which contains the full results from comparisons of seven Pressurized Water Reactors (PWRs) over multiple cycles, the authors estimate that use of the automated response time algorithms developed in this project could result in up to a 75% reduction in analysis time versus conventional manual noise analysis techniques.

**CONCLUSIONS**

Advances in robust OLM technologies include new algorithms that enable automated real-time analysis of sensor calibration and response time. Evaluation of algorithms described in this paper using laboratory flow loop measurements has shown the potential for early detection of drift in sensors, the ability to provide virtual sensors, and automating noise analysis to provide accurate estimates of sensor response time. Comparisons with manual approaches indicate a potential cost savings of about 75% using such techniques, though these cost savings estimates need to be verified using additional case studies. Future research will firm up these estimates by evaluating the algorithms using real-world (nuclear plant) process data, and assess the ability to quantify uncertainty in OLM.

Outcomes of the research described herein lay the groundwork for wider deployment of advanced OLM in U.S. nuclear facilities by developing a methodology to: 1) support the regulatory basis for OLM-based calibration assessment, 2) provide the high-confidence levels needed for sensor-fault detection, 3) provide virtual sensor estimates with meaningful confidence, and 4) integrate response-time testing of pressure transmitters with the OLM framework. These advances will provide a complete picture of health, reliability, accuracy, and speed of response of process instrumentation in legacy and future nuclear facilities and are expected to improve safety, reliability, and economics of current and planned nuclear energy systems by enabling targeted instrumentation maintenance actions during planned outages.

TABLE I. Example Automated Response Time Results (AR) Versus Manual Analysis

| | | **Automated AR** | | | **Manual Noise Analysis** | | |
|---|---|---|---|---|---|---|---|
| **Item #** | **Tag** | **2016** | **2015** | **2013** | **2016** | **2015** | **2013** |
| 1 | TAG001 | 0.26 | 0.29 | 0.27 | 0.27 | 0.27 | 0.27 |
| 2 | TAG002 | 0.31 | 0.33 | 0.30 | 0.31 | 0.31 | 0.32 |
| 3 | TAG003 | 0.29 | 0.27 | 0.27 | 0.28 | 0.28 | 0.26 |
| 4 | TAG004 | 0.35 | 0.37 | 0.38 | 0.34 | 0.35 | 0.33 |
| 5 | TAG005 | 0.29 | 0.32 | 0.26 | 0.27 | 0.27 | 0.27 |
| 6 | TAG006 | 0.29 | 0.30 | 0.31 | 0.28 | 0.29 | 0.28 |
| 7 | TAG007 | 0.21 | 0.24 | 0.23 | 0.23 | 0.23 | 0.24 |
| 8 | TAG008 | 0.27 | 0.30 | 0.28 | 0.28 | 0.28 | 0.28 |
| 9 | TAG009 | 0.24 | 0.26 | 0.26 | 0.24 | 0.23 | 0.25 |
| 10 | TAG010 | 0.20 | 0.23 | 0.22 | 0.20 | 0.21 | 0.20 |

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## REFERENCES

1. J.B. COBLE, P. RAMUHALLI, L.J. BOND, J.W. HINES, and B.R. UPADHYAYA, "Prognostics and Health Management in Nuclear Power Plants: A Review of Technologies and Applications," PNNL-21515, Pacific Northwest National Laboratory, Richland, Washington (2012).
2. "On-line Monitoring of Instrument Channel Performance," TR-104965-R1 NRC SER, Product No. 1000604, Electric Power Research Institute, Palo Alto, California (2000).
3. J.B. COBLE, R.M. MEYER, P. RAMUHALLI, L.J. BOND, H.M. HASHEMIAN, B.D. SHUMAKER, and D.S. CUMMINS, "A Review of Sensor Calibration Monitoring for Calibration Interval Extension in Nuclear Power Plants," PNNL-21687, Pacific Northwest National Laboratory, Richland, Washington (2012).
4. H. HASHEMIAN, "The State of the Art in Nuclear Power Plant Instrumentation and Control," *International Journal of Nuclear Energy Science and Technology*, **4**, *4*, 330 (2009).
5. J. W. HINES, D. GARVEY, R. SEIBERT, and A. USYNIN, "Technical Review of On-line Monitoring Techniques for Performance Assessment, Volume 2: Theoretical Issues," U.S. Nuclear Regulatory Commission, Washington, D.C.2008.
6. P. RAMUHALLI, et al., "Robust Online Monitoring Technology for Calibration Assessment of Transmitters and Instrumentation," PNNL-26919, Pacific Northwest National Laboratory, Richland, Washington (2017).