ROBUST ONLINE MONITORING FOR CALIBRATION ASSESSMENT OF TRANSMITTERS AND INSTRUMENTATION

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ABSTRACT

Robust online monitoring (OLM) technologies are expected to enable the extension or elimination of periodic sensor calibration intervals in operating and new reactors. 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. In this paper, we discuss an overview of research being performed within the Nuclear Energy Enabling Technologies (NEET)/Advanced Sensors and Instrumentation (ASI) program, for the development of OLM algorithms to use sensor outputs and, in combination with other available information, 1) determine whether one or more sensors are out of calibration or failing and 2) replace a failing sensor with reliable, accurate sensor outputs. A Gaussian Process (GP)-based uncertainty quantification (UQ) method previously developed for UQ in OLM, was adapted for this purpose. The resulting models are being evaluated for use in high-confidence signal validation for the purpose of detecting and diagnosing sensor faults, and for computing virtual sensor outputs that may be used as a temporary replacement for failing sensors. In addition to assessing sensor drift, approaches for extracting sensor response time in an automated fashion were developed, for monitoring changes in sensor response time in pressure transmitters. Such changes are also indicative of various fault modes. These algorithms were evaluated with existing measurement data from several laboratory-scale flow loops. Ongoing research in this project is focused on further evaluation of the algorithms, optimization for accuracy and computational efficiency, and integration into a suite of tools for robust OLM that are applicable to monitoring sensor calibration state in nuclear power plants.

Key Words: online monitoring; uncertainty quantification; virtual sensors; sensor response time; fault detection.

1 INTRODUCTION

Safe, economical, and reliable operation of nuclear facilities, including nuclear power plants (NPPs), fuel-fabrication facilities, and used-fuel processing facilities, relies on accurate, reliable, and timely measurement of key process variables for monitoring and control. Maintaining accurate, precise, and responsive sensors is critical to providing the process data necessary to operate these nuclear facilities. The current industry practice for maintaining the health of these sensors is highly intrusive, expensive, and inefficient [1]. This process is carried out every 18–24 months and requires the removal, recalibration, and reinstallation of every sensor and associated channels as specified in the Technical Specification (TS) and regulated by the U.S. Nuclear Regulatory Commission (NRC) [2]. This recalibration process can introduce errors in previously healthy sensors and transducers. 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 time-directed maintenance approach can be overcome using condition-based maintenance. In a condition-based maintenance paradigm, recalibration is performed only on sensors that exhibit calibration issues, and that are identified using OLM [3]. OLM can facilitate continuous or near-continuous assessment of sensor calibration while the reactor or facility is operating. Only sensors that are determined to be out of calibration or trending to be out of calibration specifications are recalibrated at the next recalibration opportunity. Hence, condition-based maintenance presents the possibility of extending and eventually eliminating scheduled periodic recalibration activities over multiple reactor cycles.

Previously proposed OLM calibration assessment programs rely on periodic recalibration of a reduced set of sensors, typically one sensor in each redundant sensor group [2]. As NRC moves towards risk-informed regulations [4], the establishment of surveillance frequency is moved from the purview of the license technical specifications to licensee control through regulatory modifications such as TSTF-425 Rev.3 [5]. TSTF-425 can form the basis for calibration interval extension and relaxation of even limited periodic calibrations once the identified technical gaps are addressed [1].

OLM uses a model of the process to provide error-corrected estimates of the true process parameter values; these predictions are assumed to be more accurate than sensor measurements that may be affected by sensor degradation. The credibility of the model predictions requires that the uncertainty in the process estimates be quantitatively bounded and accounted for in the fault-detection process. The capacity of an OLM system to detect calibration errors relies heavily on two factors: predictive uncertainty and auto-sensitivity [6]. The uncertainty in the predicted value limits the capacity of the OLM system to detect faults at levels below its inherent uncertainty. Predictive uncertainty of OLM systems must be quantified and minimized in order to make effective decisions based on these systems with high confidence [7].

UQ also forms the basis for various other requirements identified by safety evaluation reports on matters varying from fault differentiability to determination of OLM acceptance criteria [6]. These requirements have limited the application of OLM methods in the current U.S. fleet, though the U.S. nuclear industry is currently working to develop a generic basis for OLM implementation, which will allow plants to collectively switch from time-based calibrations to OLM.

A series of technical gaps associated with robust next-generation OLM are described in [8]. While several of these issues have been the subject of research over the years (with one or more commercially available products), the underlying gaps associated with a formal assessment of uncertainty and its incorporation into acceptance criteria remain. Work being conducted under this project is focused on addressing these remaining issues.

In this paper, we briefly describe ongoing research for incorporating UQ methods into the fault diagnostics arena. Additional details on the research, specifically focused on signal validation for fault diagnostics and virtual sensors for temporary replacement of faulty sensor data are available in articles submitted to this conference [9-11].

2 HIGH-CONFIDENCE SIGNAL VALIDATION

The capacity of an online monitoring (OLM) system to detect faults relies heavily on two factors, namely predictive uncertainty and auto sensitivity [6]. The ability to detect faults in calibration and changes in the process depend on the selection of an appropriate drift limit/acceptance criterion that sets the allowed level of process variability and drift in the parameter as observed by the sensor. It can be inferred that the level of uncertainty in the predicted value acts as a limit to the capacity of the OLM system to sense faults at levels below the inherent uncertainty. Hence, accurate quantification of uncertainty in OLM predictions is necessary to establish system performance and detection limits.

A multi-tier Bayesian Inference model was developed to fit the high accuracy signal validation requirements set on OLM systems that are developed for instrumentation calibration applications in NPPs. The technique utilized measured process data from plants and the associated OLM predictions as inputs to learn the statistical characteristics of various errors of interest. The types of error and their statistical properties were chosen to represent practical behaviors encountered over instrumentation life spans.

The method defines the parameters of interest with a Gaussian Process (GP) whose mean and covariance function are characterized by prior probability distributions [10]. Based on this, a posterior distribution on the GP parameter is established by non-parametric learning. By sampling from the posterior distribution various estimates of the GP predictions are made. There are many ways to create the posterior model, including Genetic Algorithm, Gibb's sampling and Markov Chain Monte Carlo sampling [12].

Our analysis focuses on the residual between the OLM model and the measured process parameters, which can indicate sensor drift or other degradation; the posterior distribution of these residuals may be inferred while accounting for the various uncertainty terms within the proposed framework.

Uncertainty terms captured in this model are:

1. **Model Inadequacy**. This includes errors that occur due to the response of the model to the noisy or uncertain input data.
2. **Observation Error**: This quantifies the error in the observed data, which could be due to sensor calibration issues, measurement errors, and stochastic variability of the underlying process.
3. **Sensor Degradation Error**: This accounts for the error term that originates when the sensor of interest experiences a fault. The statistical properties of this error term varies with time.

The proposed framework was applied to an auto-associative kernel regression (AAKR) OLM model, with the residual (difference between the model output and the actual sensor measurement) represented using multiple GPs. The AAKR is a nonparametric, memory-based zero-order model that uses memory vectors to estimate the error-corrected version of a new observation [13].

Figure 1 provides an example of the results from this approach, when applied to sensor data from a laboratory-scale flow loop. As seen from this figure, the model inadequacy error predictions for this sensor are sensitive to the drift in the OLM predictions. This may be attributed to the lack of a repository to contain the nonstationary error in the model, leaving the model inadequacy to follow the OLM prediction error; investigation of methods to improve the robustness of the model to sensor faults is ongoing.

In regions where operational transients exist, AAKR models tend to have higher predictive error, and the Bayesian UQ model predicts the model inadequacy error with much lower variability there by validating the stationary behavior that has been expected of it (Fig. 2). This behavior is primarily due to the fact that the AAKR model is trained with data over to all ranges, including any operational transients.

Additional details of the approach, along with results, are presented in [9, 10].

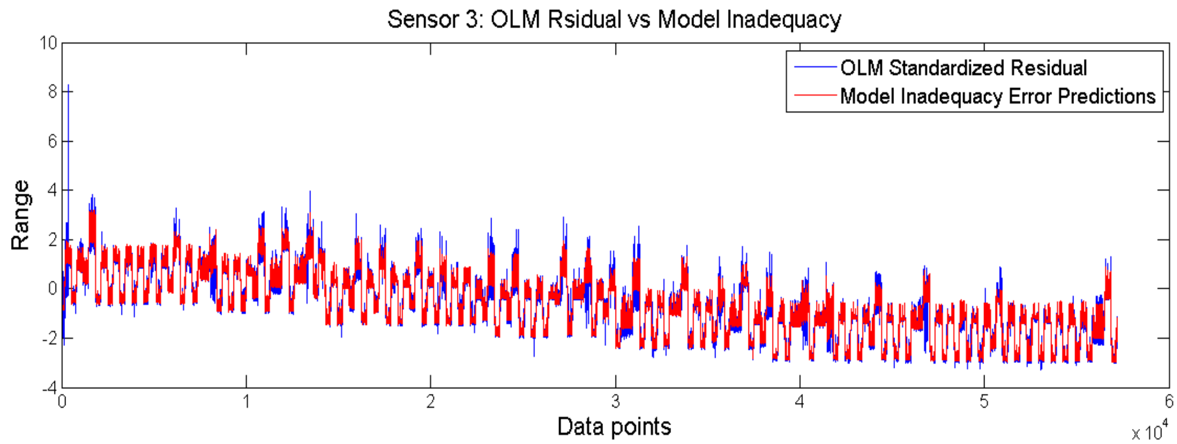

Figure 1. Model Inadequacy Error is seen to be sensitive to OLM residual drift.

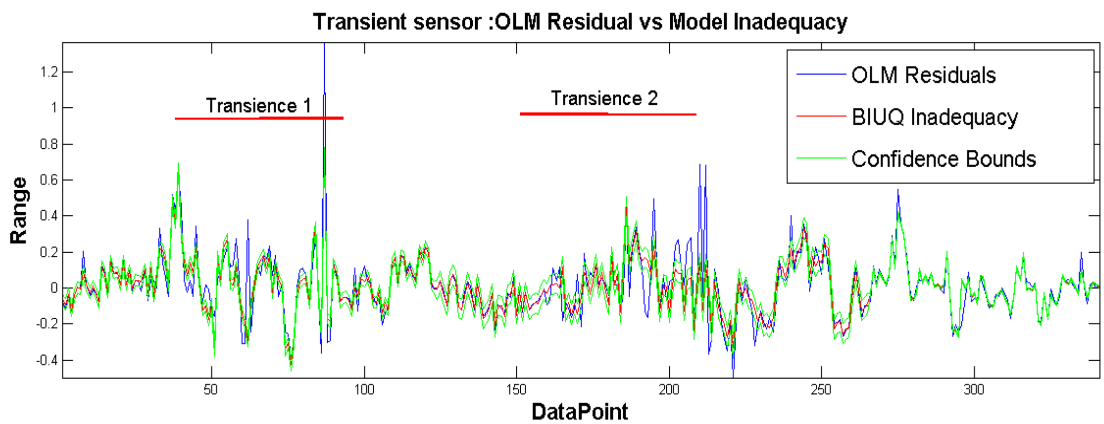

Figure 2. OLM Residual and Model Inadequacy Characterization for Transients.

3 VIRTUAL SENSING

A virtual sensor is a software tool that uses measurements from available physical sensors to compute the sensor output from an unfaulted sensor. Such software tools can serve as a sensor for an unobserved quantity of interest, or as a temporary replacement for a faulty sensor. Fundamental to the virtual sensor is the ability to predict the output from a sensor of interest using measurements from available physical sensors. Such sensor output prediction may be obtained using one of the many models used in OLM. However, given the potential need to fully characterize the uncertainty in this prediction, this study explored the use of GP models for this purpose. Measurements from physical sensors are used to estimate the parameters of the GP models. Assuming approaches to sensor-fault detection are available, the measured data from the faulty sensor may be replaced with the quantity estimated from the GP model.

Figure 3 shows an example of a virtual sensor output, for a failing (drifting) differential pressure sensor (labelled FT-3-2 in the figure, based on the assigned sensor ID) from a flow loop. The fault is simulated here as a step-wise change in the calibration. The GP model, using several of the other sensors in the flow loop, is used to estimate the true sensor value along with the confidence bounds. These quantities are relatively constant over the duration of the experiment and track well with the known true value of the sensor output (given by the sensor output during the first 500 time steps). Additional details are available in [11, 14].

The approach, however, has been shown to be sensitive to the training data set (and operational conditions represented therein) used to determine model parameters, and alternative models are being explored to address this issue.

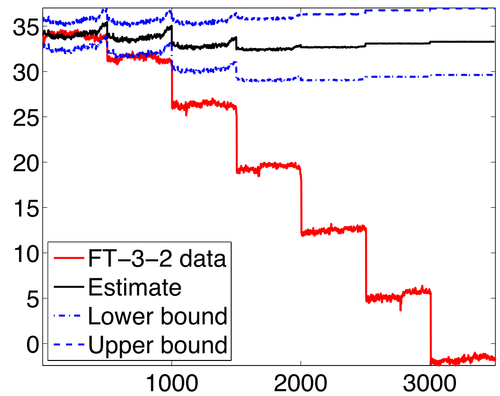

Figure 3. Gaussian Process Predictions (black, with confidence bounds in blue) for a Drifting Sensor (red)

4 RESPONSE TIME MONITORING

One of the objectives of this study is to develop a general framework for online response-time assessment for current and future NPP sensors and instrumentation. Automated noise analysis methodologies for nuclear-grade pressure and temperature sensors are being developed for this purpose. For the purposes of automating the model-fitting, the dynamic response of the sensor data (in the form of noise analysis power spectral density; PSD) was evaluated using autoregressive (AR) modeling. Various AR methods were evaluated, and in general each method solves for the AR coefficients by minimizing error terms.

Generally, the various AR methods result in very similar coefficients; however, AR modeling works best when used on data that resides in a narrow frequency band. Therefore, the wide band data generally acquired with OLM data acquisition systems was trimmed to form narrow band data to maximize the efficiency of the AR modeling. In this way, the approach is focused on limiting data provided to the AR model in order to constrain the solution to the dominant features in the PSD of the data.

Figure 4 presents an example of this windowing process. The PSD shown in Figure 4 (top) is a typical example of the wide band data acquired for analysis. If all the data used to create the wide band PSD was given to the AR algorithm, the results will be dominated by the low frequency fluctuation in Region A and also the high frequency fluctuation in Region B. To avoid these limitations of the AR technique, the OLM analyst selects a narrow band frequency window in the wide band PSD between Regions A and B that includes the dominant parts of the PSD roll-off, as shown in Figure 4 (bottom).

After the narrow band data is selected, it is analyzed by the various AR methods. The results of the combinations of parameters are evaluated and the order and method combination that produces the best fit and minimum error for the narrow band data is then chosen. After the AR parameters are determined, they are posted to the OLM database for future reference. If baseline data records already exist, then a comparison can be made to determine if there is any dynamic change in the sensors. If this is the first data record for a particular sensor, then results from other sensors in the same service can be inter-compared to assess the health of the sensor.

A comparison of the automated response time OLM methodology to manual noise analysis as well as the “gold standard” hydraulic ramp test showed that, with a couple of exceptions, the automated approach generally agrees with the ramp test data to within about a hundred milliseconds, as does the manual approach [15]. This indicates that the automated approach is generally feasible, though parameter optimization may be necessary to address the outliers.

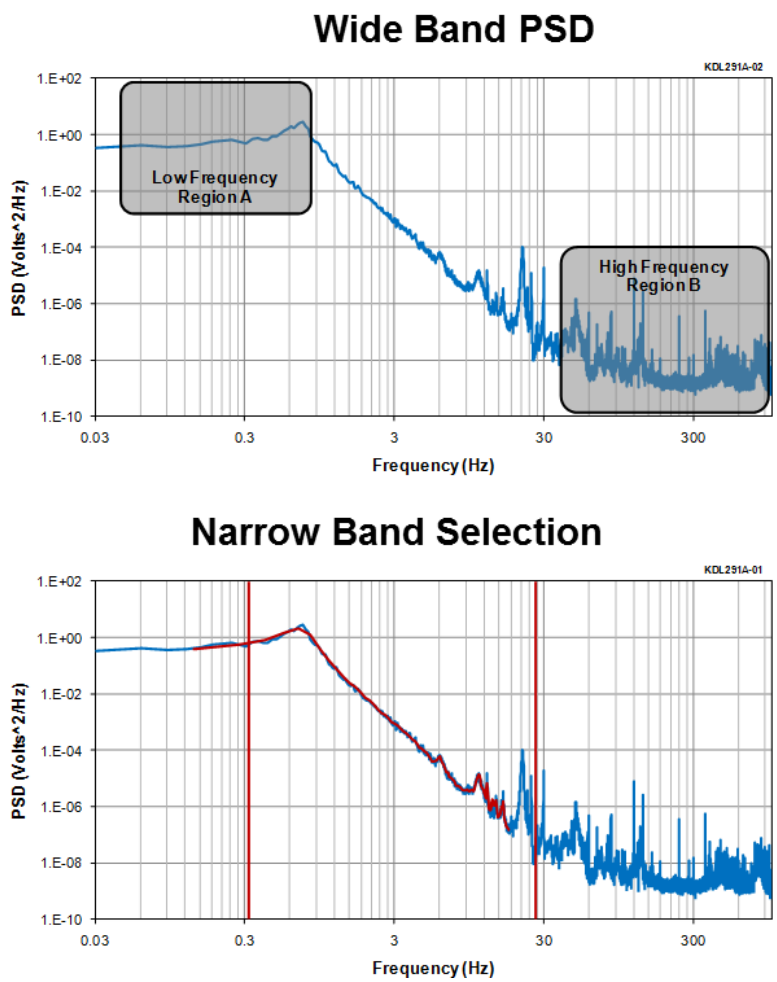

Figure 4. PSD ‘Windowing’ for Automated Noise Analysis

5 TEST AND EVALUATION

The various algorithms under development in this study were being evaluated using data from multiple flow loops. Of these, a light water test platform designed to simulate steady-state and transient fluid system conditions under forced flow and natural circulation conditions is currently being used for generating OLM data. This loop allows researchers to independently vary process conditions such as flow rate, temperature, and pressure across a relatively wide range of operating conditions. A detailed description of this loop is given in a previous technical report [15]; here, we provide a brief overview.

The flow loop is composed of two major sub-systems: (1) the primary water loop where the majority of research tasks are focused and (2) the secondary cooling loop, which serves to provide a constant temperature heat sink for the primary loop. A simplified piping and instrumentation diagram and visual representation of the loop are shown in Figure 5. The primary loop has over 200 instrumentation ports and serves as a source of OLM data. The primary loop is a closed system capable of being pressurized up to 1.03 MPaG while the secondary loop is atmospheric.

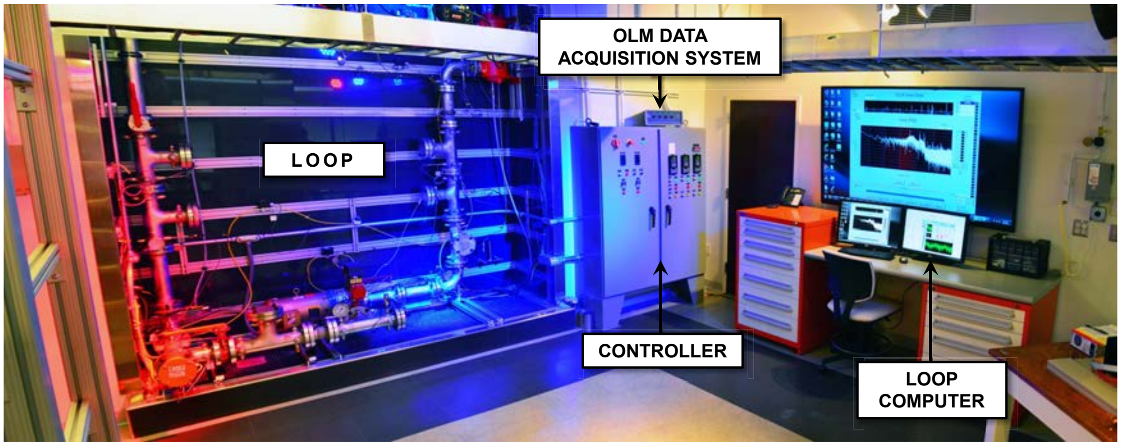

Figure 5. Analysis and Measurement Services, Corp. Flow Loop and Test Facility

Major components of the primary loop include a 7.5 horsepower centrifugal pump, 20 kW electric heater, electromagnetic (EM) flow meter, ultrasonic flow meter, pitot tube flow meter, pressurizer vessel, and a four-pass shell-and-tube heat exchanger. The primary (hot) fluid is water, which moves through the shell side of the heat exchanger. The secondary (cold) fluid is a 60/40% solution of water and propylene glycol, which flows through the heat exchanger tubes. The secondary loop contains a 26 kW industrial chiller and a magnetic flow meter.

Control of the loop pressure is through a proportional-integral-differential (PID) controller that uses feedback from a static pressure transducer and drives two fine-control flow valves. The loop temperature is controlled using a temperature PID controller, 20 kW electric heater, and a shell-tube heat exchanger. Finally, the primary loop motor speed directly controls the flow rate. The speed of the motor is proportional to the frequency of the input power, which is controlled by a variable frequency drive to regulate the input power frequency. Flow from the primary pump can also be varied by changing the position of the pump discharge pressure valve.

Instrumentation is available in the flow loop to measure temperature, flow, and pressure. Temperature indication is available from over 30 different resistance temperature detector (RTD) and thermocouple sensors. Flow measurement is available through four different methods – an inline electromagnetic flow tube, a clamp-on ultrasonic flowmeter, a pitot tube and a venturi flow meter.

The pressure and differential pressure sensors are piped into the flow loop using 3/8 in. stainless steel sensing lines with high point vent, loop isolation, and manifold throttling capability. The 3/8 in. sensing line was selected to properly model sensing line effects and signal transmission characteristics expected in most NPP installations. Sensing line design allows for throttling to simulate blockages and void introduction using a known quantity of air at standard temperature and pressure.

Other flow loops used in the test and evaluation include smaller loops at the University of Tennessee and at Analysis and Measurement Services, Corp. that were used for preliminary data generation on a range of sensor and process faults. Details of these are provided in various publications [15].

6 SUMMARY AND FUTURE WORK

Several advances were made in algorithms for robust OLM. Implementation and testing of a robust signal validation approach was completed during this phase of the project, as was the identification and preliminary testing of algorithms for virtual sensing in an OLM context. Both sets of algorithms are data-driven, and require data sets for deriving the algorithm parameters.

In the case of signal validation, a GP-based UQ method was adapted for sensor-fault detection. The adaptation to signal validation is based on a framework that enables quantification of discrepancies between a previously tuned OLM model and observed data and the associated uncertainty. The framework enables incorporation of knowledge about different sources of error and uncertainty that can lead to these discrepancies. Evaluation results using available flow loop data indicate, in addition to the stationary components in the model residual, the nonstationary sensor degradation will likely need to be explicitly included.

The virtual sensing approach evaluated GP models; the results to date indicate that models relying on measured sensor data as inputs are sensitive to the training data set used to estimate the model parameters. This is not surprising, as the presence of faulty sensor data in the training data set can skew the virtual sensor results. Using independent data, such as control sensor measurements, as the inputs to virtual sensing algorithms appears to improve the virtual sensor prediction.

Noise analysis appears to provide a reliable approach to testing sensor response time, particularly for pressure transmitters. Modifications to the response time analysis method, to enable automating the technique, were developed and evaluated using both flow loop data as well as plant data. The results indicate that this approach provides results that are close to those obtained using manual analysis methods, and are generally within the tolerance observed in nuclear-grade pressure transmitters.

Ongoing work is focused on several aspects of OLM theory and implementation. Additional evaluation of the algorithms is ongoing, with evaluation criteria focused on accuracy of the sensor value prediction, computational complexity, and ability to compute uncertainty bounds. Modifications to the models used for signal validation, to address observed issues with transient data, are also underway. Response time using noise analysis is being further evaluated and will be integrated into the overall robust OLM suite of algorithms.

7 ACKNOWLEDGMENTS

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