Attachment 3

Instrument Monitoring Methods and Best Practices (Non-Proprietary)

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INTRODUCTION AND BACKGROUND

Instrumentation plays a pivotal role in providing essential data necessary for the operation and maintenance of power plant equipment. These instrument readings are equally important for assessing the health of the instrumentation, particularly as part of an online monitoring program. Hence, it's imperative that the instrumentation receives periodic testing and maintenance, operates as designed, and provides accurate and dependable inputs.

Instrument redundancy is utilized to address the potential of a single instrument failure that could impact operations or prevent actuation of the associated equipment. The OLM software application, while most often utilized to monitor equipment for factors like reliability, availability, and performance, also has the capability to monitor and verify the condition of the instrumentation used for monitoring and control/actuation of the equipment.

The OLM software utilizes predictive pattern recognition models tailored for each set of instruments in a function. These models use machine learning and “normal” data to establish relationships between redundant instruments and other correlated process parameters. Then, these relationships are continuously monitored in real time by the OLM software to identify any deviations that might indicate a potential issue with the instrument.

Additionally, the OLM software features a comprehensive suite of fault detectors specifically designed for monitoring instrument performance. [

]a,c These fault detectors, coupled with pattern recognition models, serve to continuously confirm the proper functioning of the instruments, to determine whether a calibration of the end devices in an instrument channel is required.

2 ONLINE MONITORING METHODS

Online monitoring (OLM) for assuring that an instrument is functioning properly can be implemented by a variety of methods. Classical methods include verifying that the data values obtained from the instrument remain within the reasonable range for the process conditions. More advanced methods compare the data values obtained from the instrument to a model for the expected data values given the process conditions. These models can take a variety of forms, including a comparison of the instrument values to one or more redundant instrument peers and more sophisticated advanced pattern recognition (APR) or digital twin based models.

This section compares the APR model method with methods using redundant instrument average models for use in online monitoring of instrument performance. All models discussed in this section are derived and demonstrated based on the same training data and testing data for a set of four redundant water level transmitters in a nuclear power plant's steam generator. Three of these redundant instruments are narrow range level transmitters and one is a wide range level transmitter. The training data is taken from a period when all the instruments are operating correctly. The testing data is taken from a period when one of the narrow range level transmitters experienced a drift failure. All the models are trained and run simultaneously in the OLM software. This enables a direct comparison of the predictive capability of each model type.

Pattern Recognition Method

OLM software using machine learning and APR can predict the behavior of process equipment, including instrumentation, in real-time, which facilitates the early detection of anomalous behavior. The APR models use real-time instrument data as the basis for online monitoring and inherently monitor the condition of the instruments and transmitters monitoring the process equipment. The OLM software will alert when an instrument's response to the current process conditions does not agree (within a statistical tolerance) with the APR model's predicted response for those same conditions.

The APR model's predicted response is learned from a curated set of historical data that is representative of normal or expected behavior of the monitored parameter (the "training data"). This historical data set will cover the range of expected process variation and will be chosen from time periods when instruments and transmitters are known to be acceptably calibrated. Utilizing the "training data", the OLM software uses machine learning to model the normal relationships between a chosen set of well-correlated input parameters. After the APR models are trained offline, the OLM software uses pattern recognition, based on the trained APR model, to predict the expected value of each input parameter in real-time, resulting in a predicted and observed signal for each parameter at each monitored point in time.

The difference between the observed value and the predicted value for a monitored parameter is typically called the "residual" value. Regardless of the operating state of the instrument, such as power level, or the state of other important influences, such as seasonal temperature, the residual should always have a near zero mean and stable statistics about the mean. In statistical terms, the residual time series would be termed a “stationary” signal. This attribute allows for the application of statistical models to detect abnormal behavior in the residual signal as it is calculated by the OLM software. When the residual is outside of its normal range, as shown in Figure 2-1, an alert is issued if the threshold value is reached or exceeded.

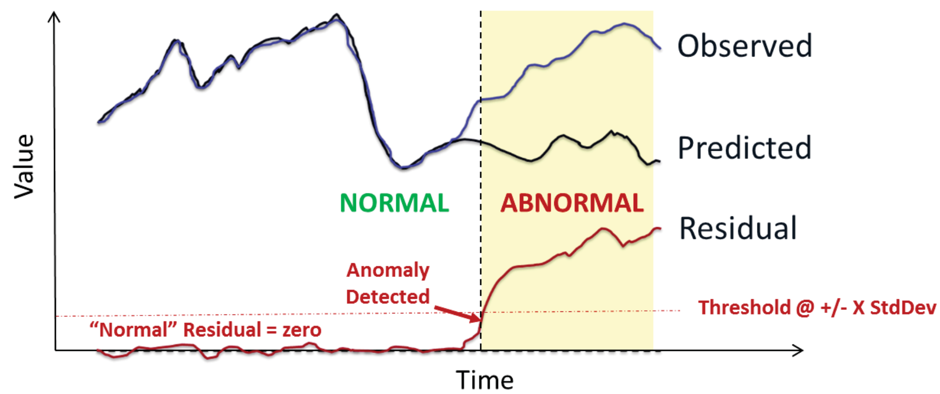

Figure 2-1: APR residual signal enables very early detection of an abnormal condition

In the following use case example, the OLM result for detecting the drift failure of a narrow range level transmitter using an APR model is presented.

Pattern Recognition Use Case Example

In this example, a single APR model is created with level transmitters LT-01, LT-02, LT-03 and LT-04 as the input parameters. Figure 2-2 illustrates the data behavior when all four redundant steam generator level instruments are normal and healthy. The red trace plots the measured values for narrow range level transmitter LT-01, the blue trace plots the measured values for narrow range level transmitter LT-02, and the black trace plots the measured values for narrow range level transmitter LT-03, and the green trace plots the measured values for wide range level transmitter LT-04. The APR model is trained using the normal and healthy data shown in Figure 2-2.

Figure 2-2 additionally illustrates four corresponding “predicted value” traces based on the APR model. The pink trace plots the APR model prediction values for LT-01, the cyan trace plots the APR model prediction values for LT-02, the magenta trace plots the APR model prediction values for LT-03, and the yellow trace plots the APR model prediction values for LT-04. As shown in Figure 2-2, the measured value traces (red, blue, black and green) lay right on top of predicted value traces (pink, cyan, magenta and yellow) rendering the predicted value traces nearly indistinguishable from the measured value traces. Since the data in Figure 2-2 was used for training the APR model, this good agreement is expected.

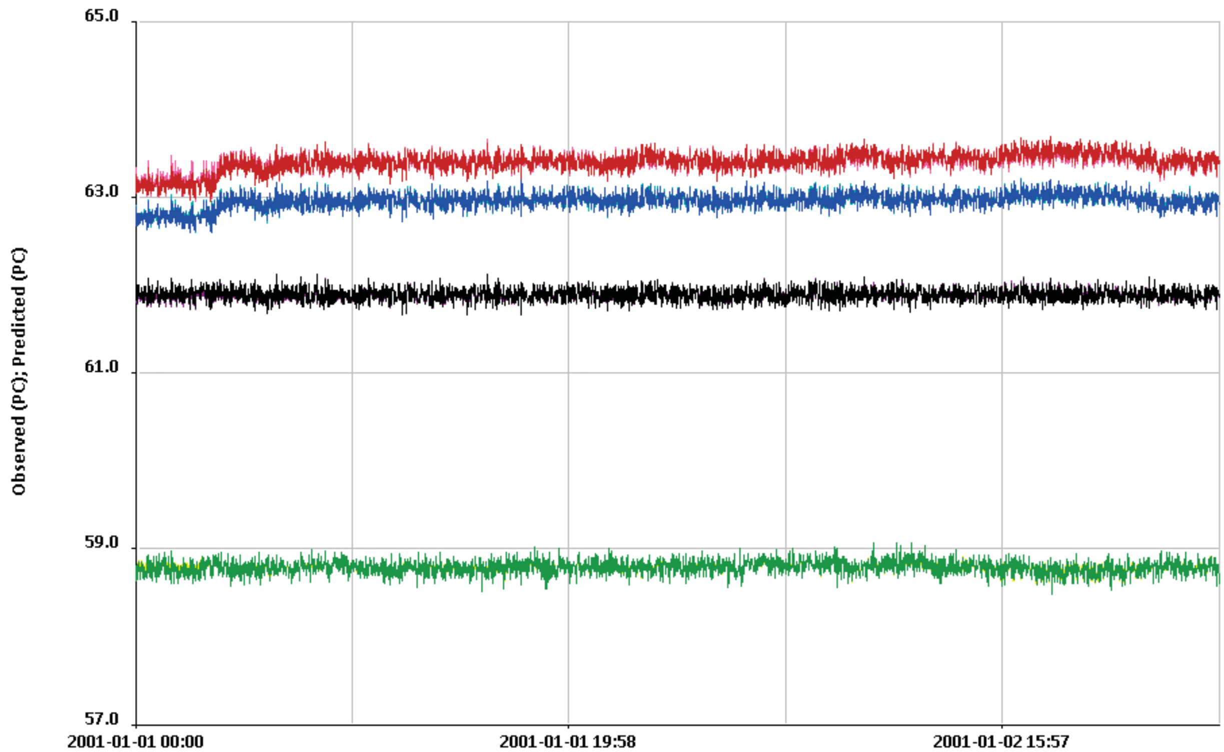

Figure 2-2: Measured and APR predicted values for a normal condition

Figure 2-3 illustrates the data behavior when drift occurs in the LT-02 narrow range level transmitter. Once again, the red trace plots the measured values for narrow range level transmitter LT-01, the blue trace plots the measured values for narrow range level transmitter LT-02, and the black trace plots the measured values for narrow range level transmitter LT-03, and the green trace plots the measured values for wide range level transmitter LT-04. The pink trace plots the APR model prediction values for LT-01, the cyan trace plots the APR model prediction values for LT-02, the magenta trace plots the APR model prediction values for LT-03, and the yellow trace plots the APR model prediction values for LT-04.

When this drift occurred, the deviation between the blue measured trace and the cyan APR predicted trace identifies the LT-02 drift. Notice that the APR predictions, including predictions for the drifting instrument, remain accurate throughout the event. [ ][a,c] The predicted value traces for LT-01, LT-03 and LT-04 remain nearly indistinguishable from the measured value traces despite the drift in LT-02. [

][a,c]

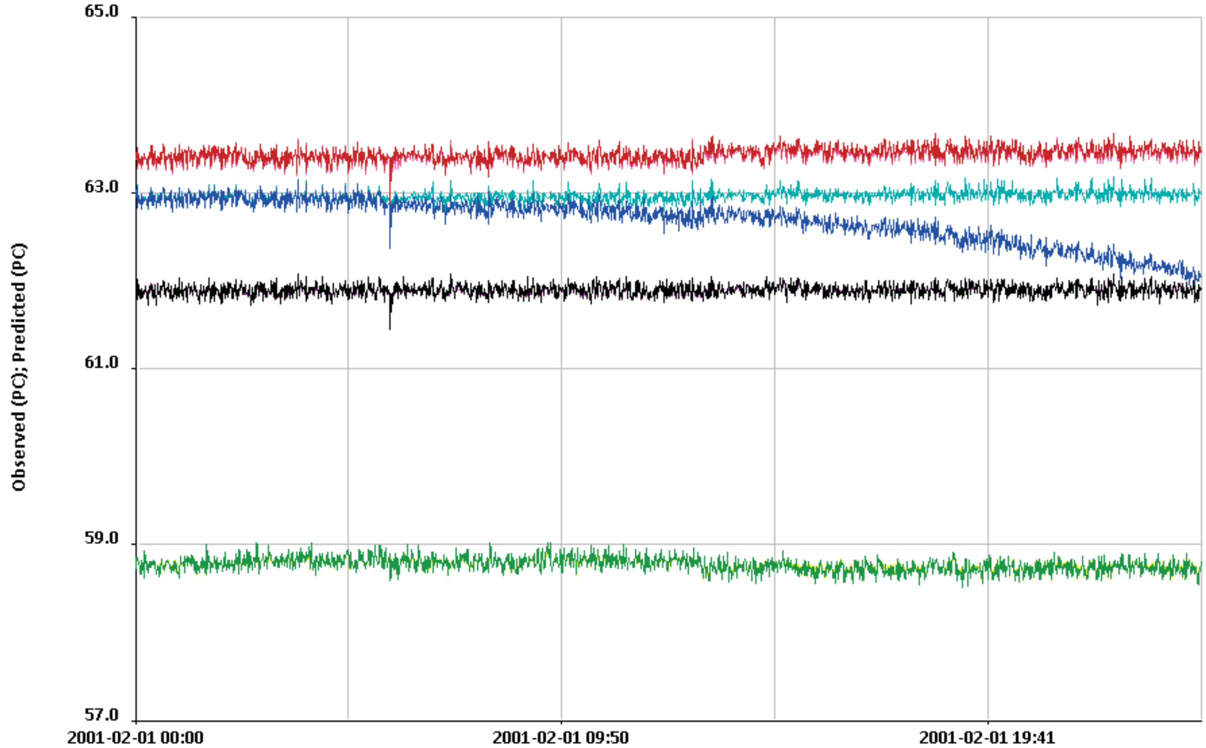

Figure 2-3: Measured and APR predicted values for a drift failure of LT-02 (blue trace)

Redundant Instrument Methods

This section describes methods for verifying instrument accuracy using several types of average based models. The case studies presented in this section use the same data as described above using an APR based model. [

]a,c

Case studies are presented in this section for (1) simple average of redundant measurements, (2) biased average of redundant measurements, (3) leave one out average of redundant measurements, and (4) consistency weighted (parity space) average of redundant measurements. Each of the methods are illustrated by a case study example for the same instrument drift failure event that is discussed above for the APR model method.

Simple Average Method

In its most simple form, an average based model of the expected value for each of the four redundant level transmitters can be constructed as the arithmetic average of the four measured values at each point in time. In this case, there is only one predicted value – the arithmetic average – at each point in time. Each of the measured values is expected to agree with the average value within a tolerance. [

]a,c

Simple Average Use Case Example

In this example, a single model is created with LT-01, LT-02, LT-03 and LT-04 as the input parameters and the simple average as the output parameter. As used for the APR model the training data and testing data for a set of four redundant water level transmitters in a nuclear power plant's steam generator was used. Three of these redundant instruments are narrow range level transmitters and one is a wide range level transmitter. The training data is taken from a period when all the instruments are operating correctly. The testing data is taken from a period when one of the narrow range level transmitters experience drift.

Referring to Figure 2-4 and Figure 2-5, the data is plotted for the four redundant steam generator level instruments along with a plot of the simple average of the four measurements. Once again, the red trace plots the measured values for narrow range level transmitter LT-01, the blue trace plots the measured values for narrow range level transmitter LT-02, the black trace plots the measured values for narrow range level transmitter LT-03, and the green trace plots the measured values for wide range level transmitter LT-04. The pink trace plots the simple average of the four measurements.

Figure 2-4 illustrates the data behavior during normal plant operation when all four instruments are normal and healthy. As noted, there is only one predicted value trace in this figure, which is the pink trace. [

]a,c

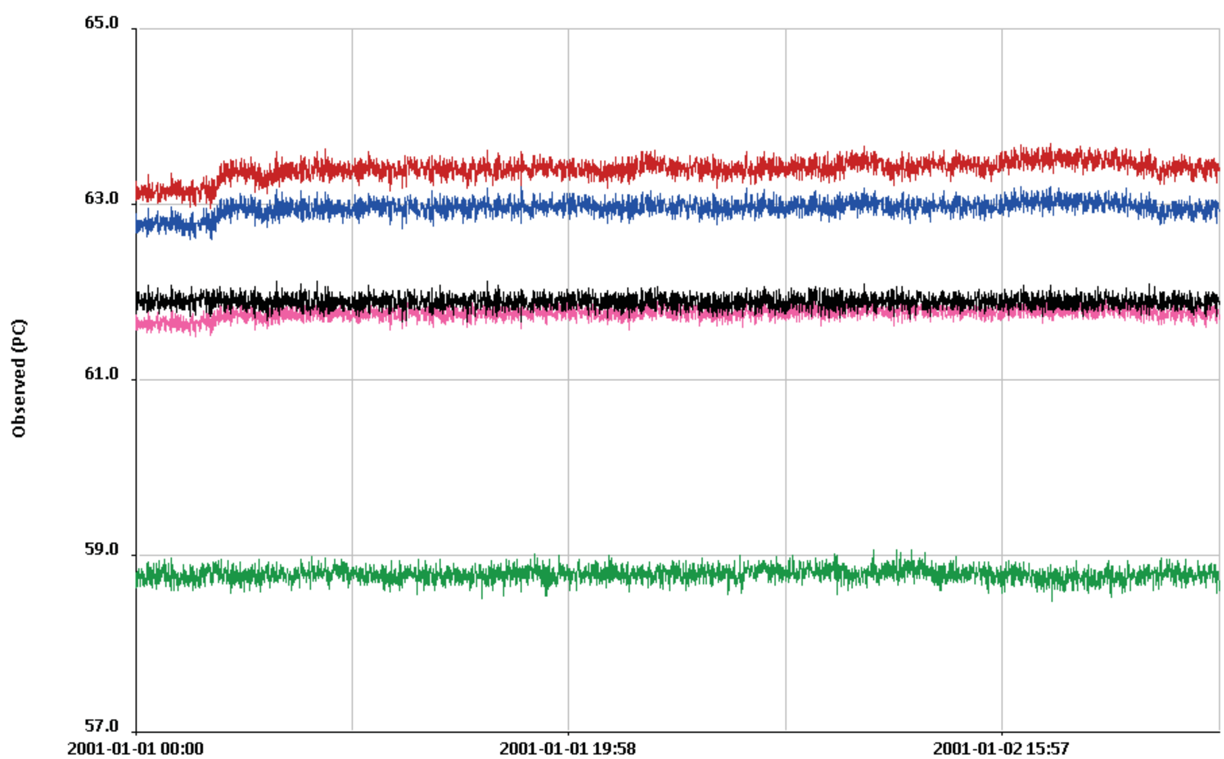

Figure 2-4: Measured and simple average values for a normal condition

Figure 2-5 illustrates the data behavior when the LT-02 narrow range level transmitter drifts. In this example, the LT-02 measurement values drift toward the simple average values and would therefore appear to be in better agreement [

]a,c

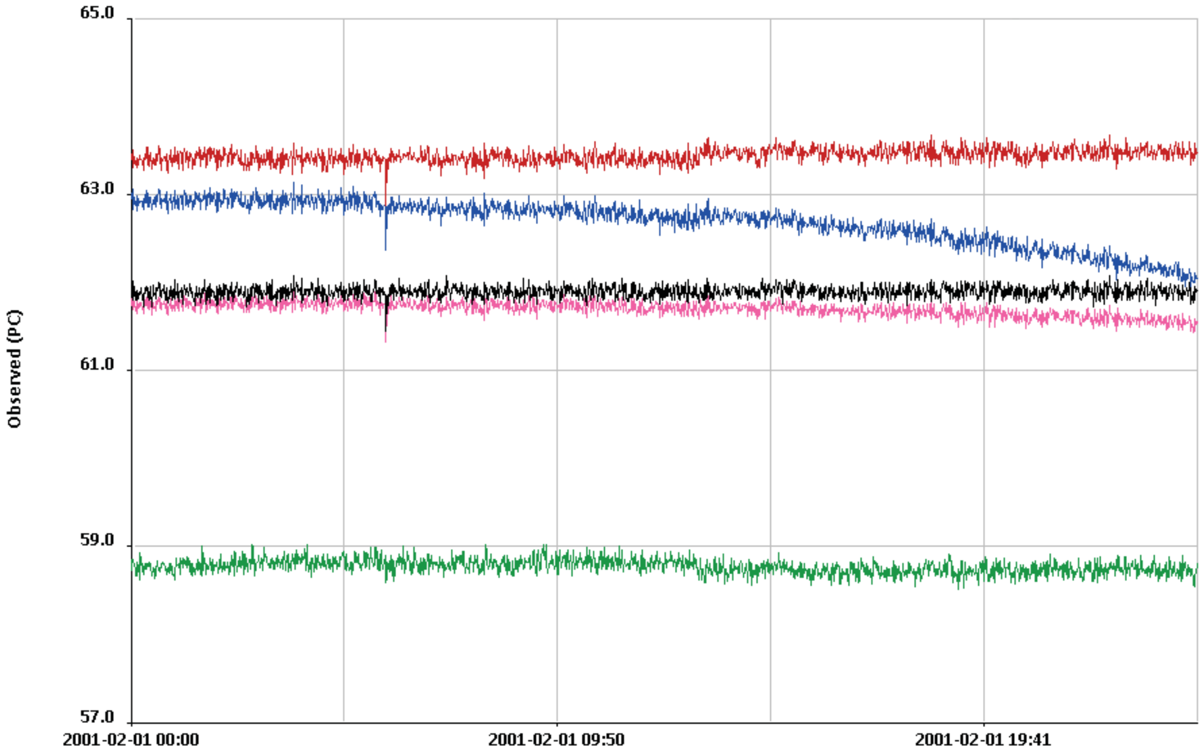

Figure 2-5: Measured and simple average values for a drift failure of LT-02 (blue trace)

Biased Average Method

Even when redundant instruments are nominally measuring the same quantity, it is often the case [

]a,c

Implicit in the biased average model is a learned bias value constant, a_i, that is unique for each redundant instrument. This results in four separate models in this example. This also requires a period of training data that can be used to [

]a,c

Biased Average Use Case Example

In this example, four models are created with LT-01, LT-02, LT-03 and LT-04 as the input parameters and the [ ]a,c for one of the inputs as the output parameter. As was done for the APR model the same training data and testing data for a set of four redundant water level transmitters in a nuclear power plant's steam generator was used. The training data is taken from a period when all the instruments are operating correctly. The testing data is taken from a period when one of the narrow range level transmitters experiences drift. The model bias values are learned from the training data [

]a,c

Referring to Figure 2-6 and Figure 2-7, data is plotted for the four redundant steam generator level instruments along with a plot of the biased average predictions for each of the four measurements. Once again, the red trace plots the measured values for narrow range level transmitter LT-01, the blue trace plots the measured values for narrow range level transmitter LT-02, the black trace plots the measured values for narrow range level transmitter LT-03, and the green trace plots the measured values for wide range level transmitter LT-04.

In addition, there are four corresponding "predicted value" traces shown in Figure 2-6 and Figure 2-7. In these figures, the pink trace plots the biased average model prediction values for LT-01, the cyan trace plots the biased average model prediction values for LT-02, the magenta trace plots the biased average model prediction values for LT-03, and the yellow trace plots the biased average model prediction values for LT-04.

Figure 2-6 illustrates the data behavior during normal plant operation when all four instruments are normal and healthy. [

]a,c Comparing Figure 2-6 to Figure 2-4, [

]a,c

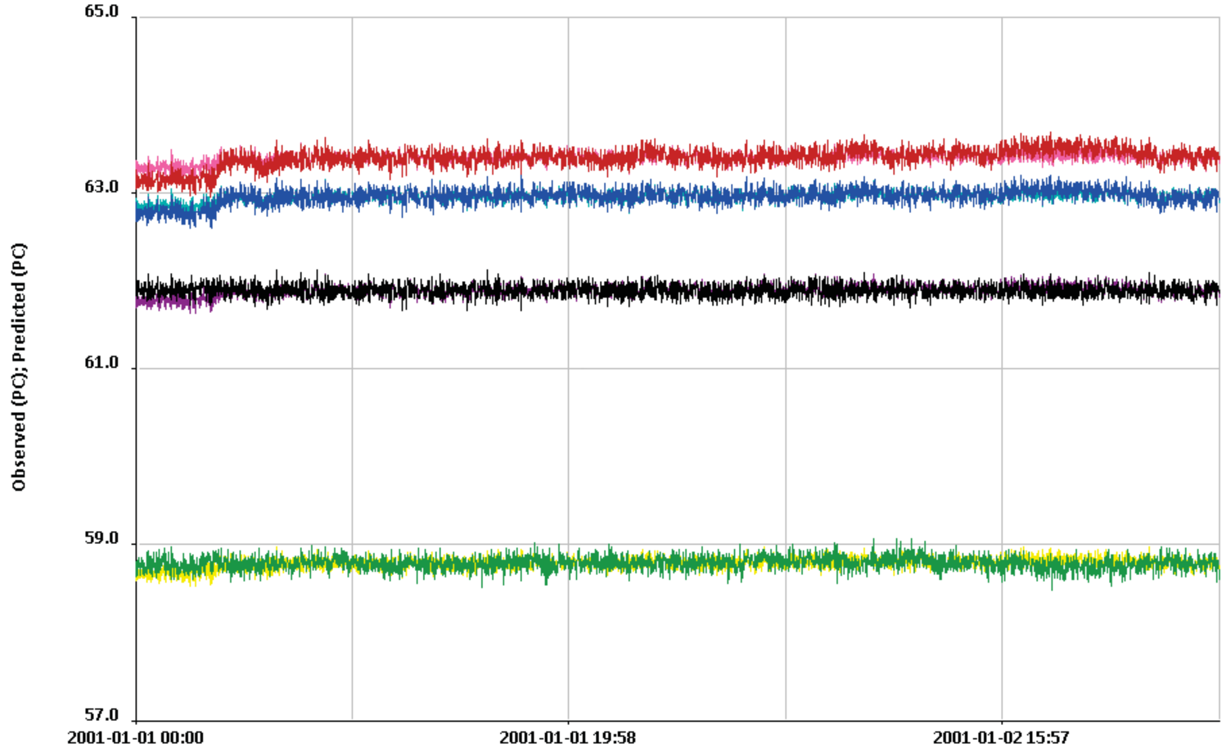

Figure 2-6: Measured and biased average values for a normal condition

Figure 2-7 illustrates the data behavior when the LT-02 narrow range level transmitter drifts. As shown in Figure 2-5, the LT-02 measurements drift toward the simple average in this example. When the transmitter drifts, the deviation between the blue measured trace and [

]a,c

Comparing the biased average model results in Figure 2-7 to the APR model results in Figure 2-3 [ ]a,c Note that the biased average models and the APR model were both trained with the same training data and both tested with the same testing data. [

]a,c

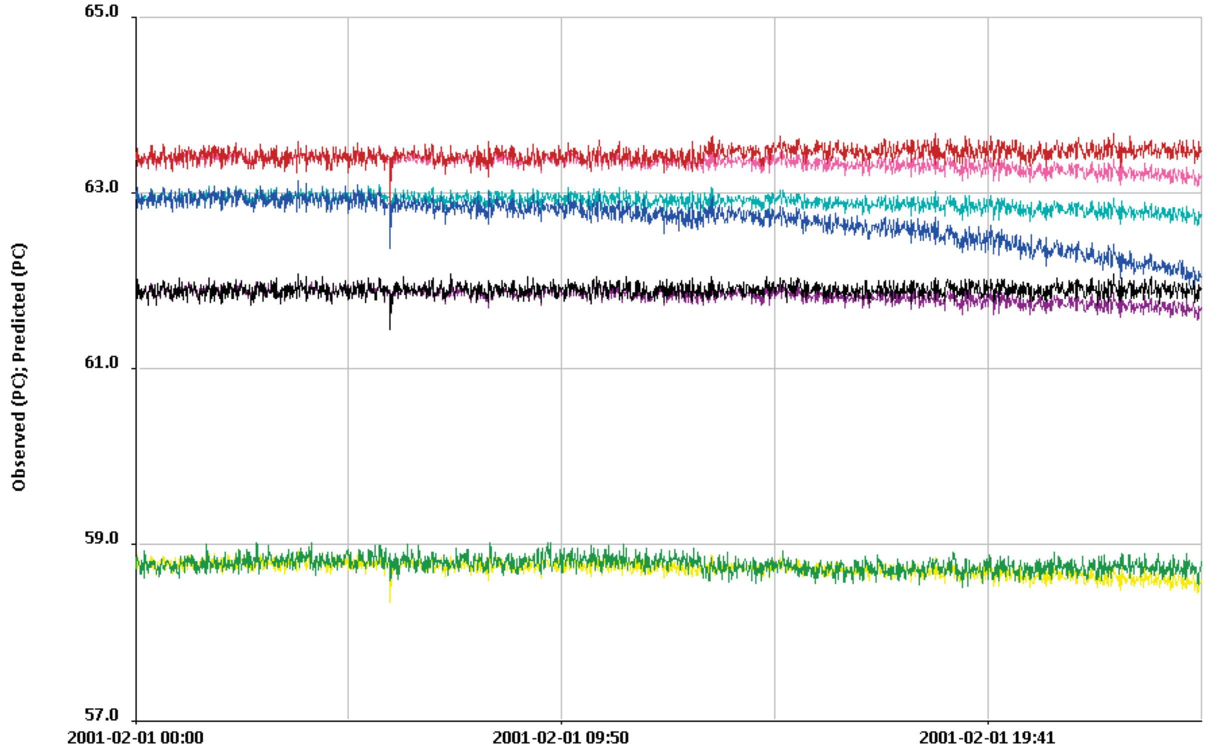

Figure 2-7: Measured and biased average values for a drift failure of LT-02 (blue trace)

Leave one out modeling is one approach often used [ ]a,c Another approach is the parity space average method, [ ]a,c These approaches are discussed in the following sections.

Leave One Out Average Method

The leave one out average method modifies the biased average method. In this model, the input parameter that is the objective for the corresponding prediction is not included in the calculation of the average. For example, the average of LT-02, LT-03 and LT-04 is used for the prediction of LT-01. The prediction bias for LT-01 is calculated from the training data using a method similar to the biased average prediction described above. This results in four separate models in this example. This also requires [ ]a,c

Leave One Out Average Use Case Example

In this example, a separate leave one out (LOO) average model is created for each of LT-01, LT-02, LT-03 and LT-04. Each model outputs a prediction parameter for the input parameter that is left out of the average. As was used for the APR model the same training data and testing data for a set of four redundant water level transmitters in a nuclear power plant's steam generator was used.

Referring to Figure 2-8 and Figure 2-9, the data is plotted for the four redundant steam generator level instruments. Once again, the red trace plots the measured values for narrow range level transmitter LT-01, the blue trace plots the measured values for narrow range level transmitter

LT-02, and the black trace plots the measured values for narrow range level transmitter LT-03, and the green trace plots the measured values for wide range level transmitter LT-04.

In addition, there are four corresponding "predicted value" traces shown in Figure 2-8 and Figure 2-9. The pink trace plots the LOO average model prediction values for LT-01, the cyan trace plots the LOO average model prediction values for LT-02, the magenta trace plots the LOO average model prediction values for LT-03, and the yellow trace plots the LOO average model prediction values for LT-04.

Figure 2-8 illustrates the data behavior during normal plant operation when all four instruments are normal and healthy. In the "normal" case, [

]a,c

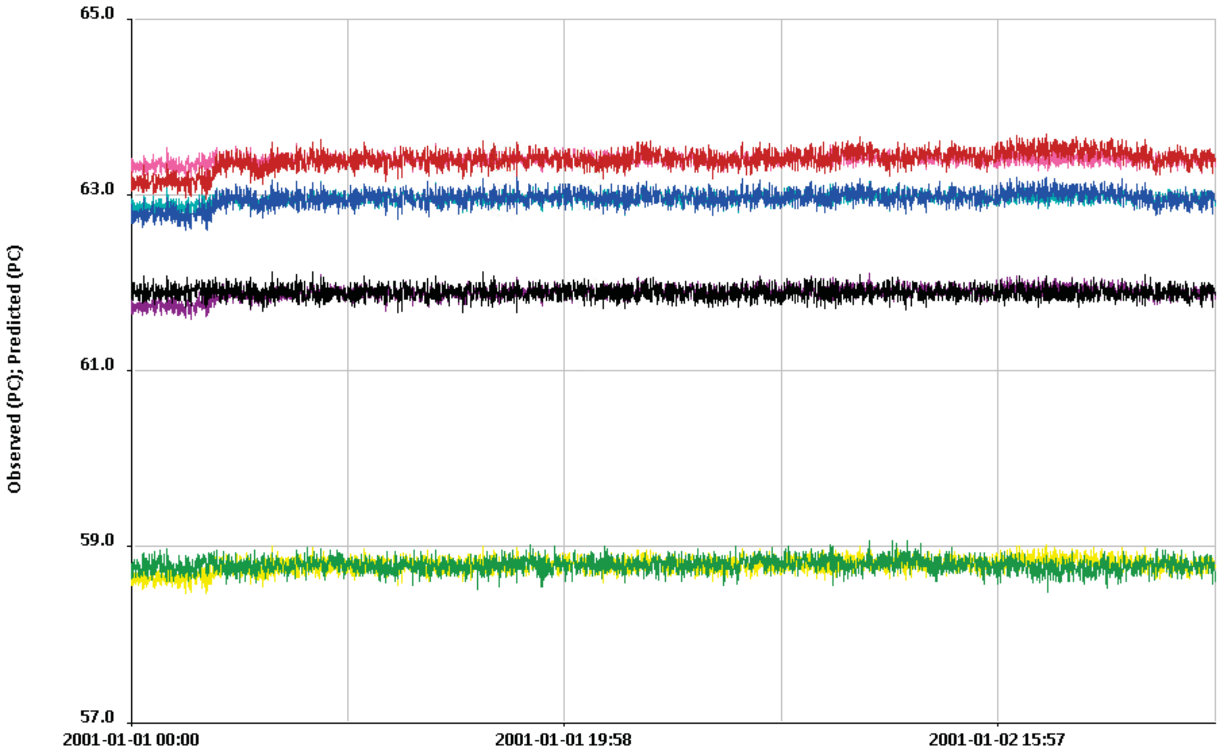

Figure 2-8: Measured and LOO average values for a normal condition

Figure 2-9 illustrates the data behavior when the LT-02 transmitter drifts . When the transmitter drifts, the deviation between the blue measured trace and [

]a,c

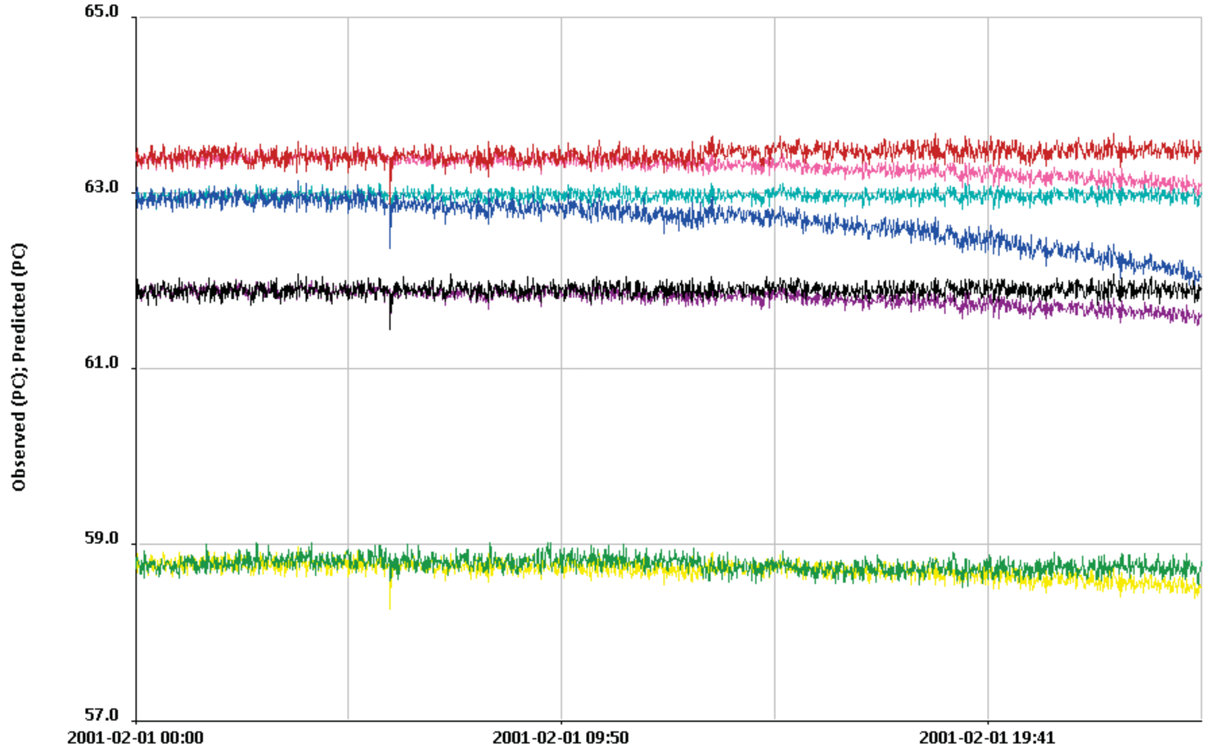

Figure 2-9: Measured and LOO average values for a drift failure of LT-02 (blue trace)

Parity Space Average Method

The parity space average (PSA) method [

]a,c Briefly,

[

]a,c based on each instrument's historical performance.

[

]a,c

[

]a,c

[

]a,c

[

]a,c

Figure 2-10: Parity space average model parameters learned during model training

Parity Space Average Use Case Example

In this example, a parity space average model is created with LT-01, LT-02, LT-03 and LT-04 as the input parameters. The model produces a corresponding prediction parameter for each of the input parameters. As was done with the APR model, the same training data and testing data for a set of four redundant water level transmitters in a nuclear power plant's steam generator was used.

Referring to Figure 2-11 and Figure 2-12, the data is plotted for the four redundant steam generator level instruments. Once again, the red trace plots the measured values for narrow range level transmitter LT-01, the blue trace plots the measured values for narrow range level transmitter LT-02, and the black trace plots the measured values for narrow range level transmitter LT-03, and the green trace plots the measured values for wide range level transmitter LT-04.

In addition, there are four corresponding "predicted value" traces shown in Figure 2-11 and Figure 2-12. The pink trace plots the PSA model prediction values for LT-01, the cyan trace plots the PSA model prediction values for LT-02, the magenta trace plots the PSA model prediction values for LT-03, and the yellow trace plots the PSA model prediction values for LT-04.

Figure 2-11 illustrates the data behavior during normal plant operation when all four instruments are normal and healthy. In the "normal" case, the measured and PSA predicted values agree very well, and the measured value traces lay right on top of predicted value traces.

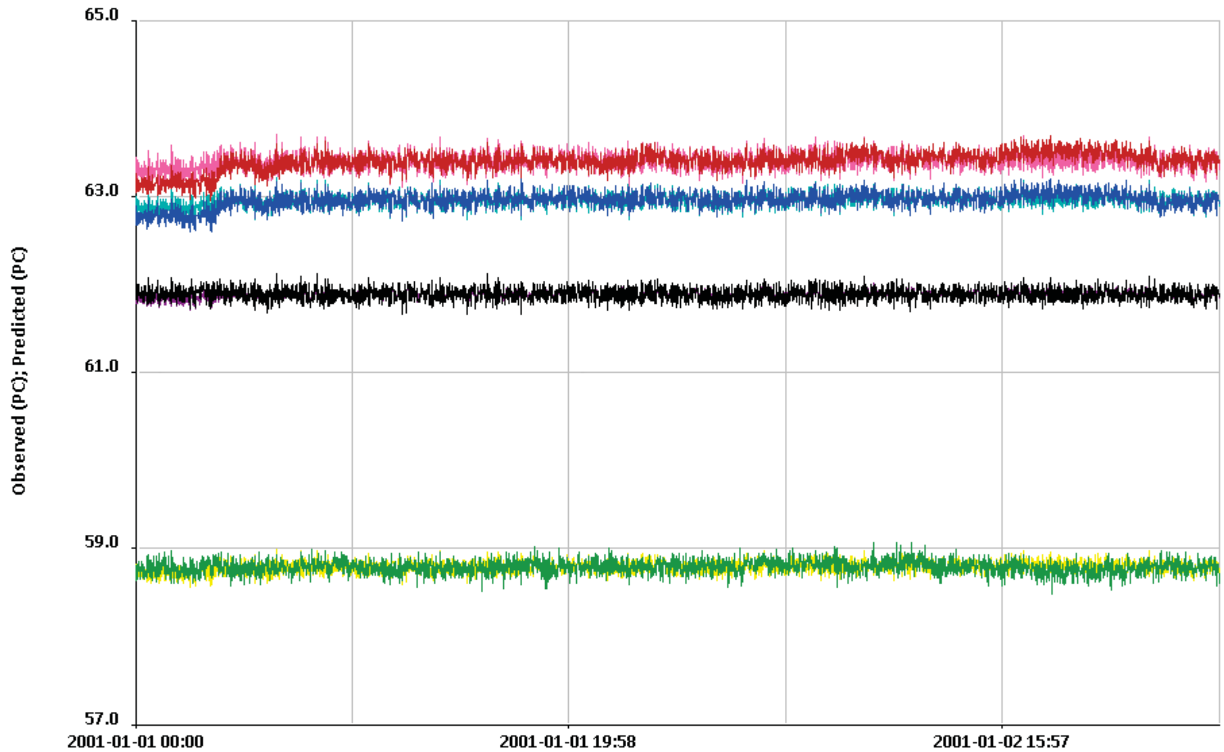

Figure 2-11: Measured and parity space average values for a normal condition

Figure 2-12 illustrates the data behavior when the LT-02 transmitter drifts. When the transmitter drifts, the deviation between the blue measured trace and the cyan PSA predicted trace [

]a,c

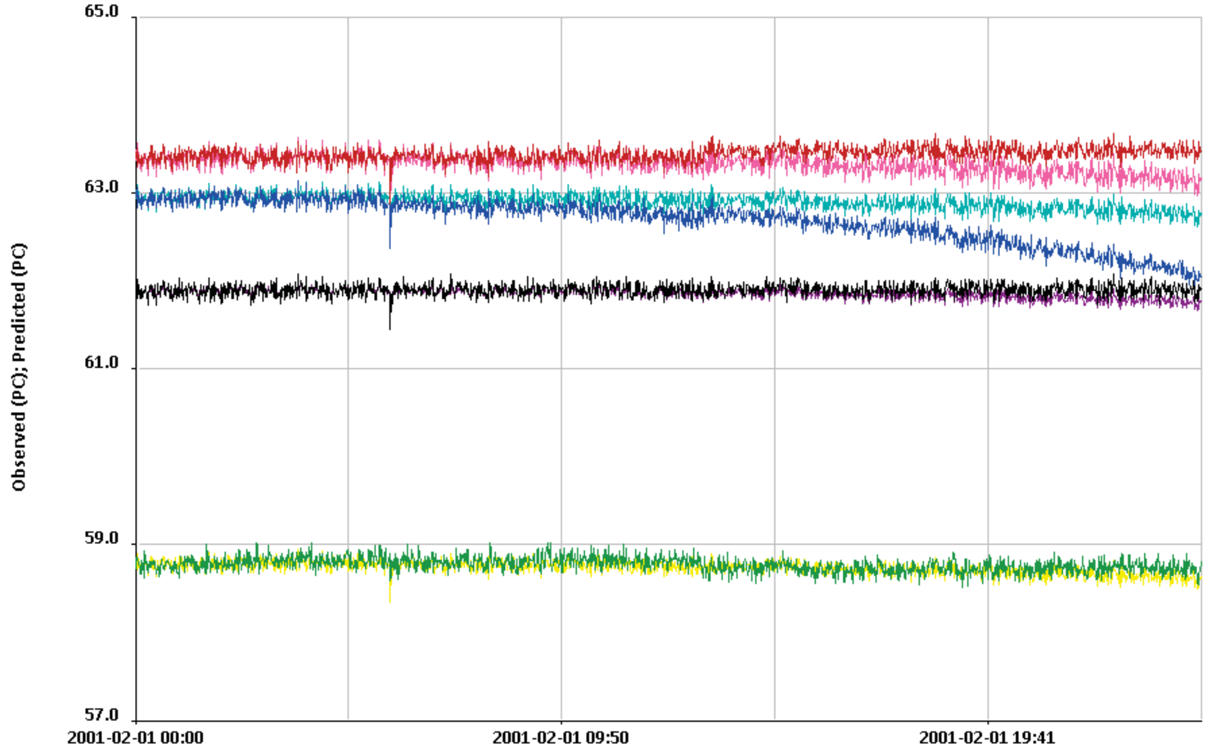

Figure 2-12: Measured and parity space average values for a drift failure of LT-02 (blue trace)

Comparing the PSA model results in Figure 2-12 to the APR model results in Figure 2-3 [ ]a,c Note that the PSA models and the APR model were both trained with the same training data and both tested with the same testing data. [

]a,c

3 CONCLUSIONS

Online monitoring (OLM) provides an effective tool for ensuring that the instrument is functioning properly. The most effective methods compare the data values obtained from the instrument to a model for the expected data values given the process conditions. These models can take a variety of forms, including a comparison of the instrument values to one or more redundant instrument peers and more sophisticated APR or digital twin based models.

This document compares the APR model methods to a variety of average based model methods for the example of drift in a water level transmitter in a nuclear power plant's steam generator. In this document, all models are constructed using only the four redundant level transmitters as the source of the modeling and monitoring data. All models are trained using data from a period of normal and healthy operation for all four instruments and for the monitored parameter. All models are tested using data from a period when drift occurs in one of the four redundant level transmitters. This example case is used to compare the performance of the APR and average based models [ ]a,c

In this example, the instrument exhibits a drift that is toward the average of the four redundant level transmitters. [ ]a,c

The OLM software provides a comprehensive capability to monitor and verify the condition of instrumentation used for monitoring and control/actuation of the equipment. The OLM software includes the capability to automatically train and use a variety of model types and fault detection methods, providing an optimal solution for instrument monitoring.