VALIDATION OF ON-LINE MONITORING TECHNIQUES TO NUCLEAR PLANT DATA

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The Electric Power Research Institute (EPRI) demonstrated a method for monitoring the performance of instrument channels in Topical Report (TR) 104965, "On-Line Monitoring of Instrument Channel Performance." This paper presents the results of several models originally developed by EPRI to monitor three nuclear plant sensor sets: Pressurizer Level, Reactor Protection System (RPS) Loop A, and Reactor Coolant System (RCS) Loop A Steam Generator (SG) Level. The sensor sets investigated include one redundant sensor model and two non-redundant sensor models. Each model employs an Auto-Associative Kernel Regression (AAKR) model architecture to predict correct sensor behavior. Performance of each of the developed models is evaluated using four metrics: accuracy, auto-sensitivity, cross-sensitivity, and newly developed Error Uncertainty Limit Monitoring (EULM) detectability. The uncertainty estimate for each model is also calculated through two methods: analytic formulas and Monte Carlo estimation. The uncertainty estimates are verified by calculating confidence interval coverages to assure that 95% of the measured data fall within the confidence intervals. The model performance evaluation identified the Pressurizer Level model as acceptable for on-line monitoring (OLM) implementation. The other two models, RPS Loop A and RCS Loop A SG Level, highlight two common problems that occur in model development and evaluation, namely faulty data and poor signal selection

KEYWORDS : Monitoring, Sensor Calibration, Diagnostics, Empirical Modeling

1. INTRODUCTION

The Electric Power Research Institute (EPRI) demonstrated a method for monitoring the performance of instrument channels in Topical Report (TR) 104965, "On-Line Monitoring of Instrument Channel Performance." The current state-of-the-art is described in the first of a three-volume NUREG/CR-6895 entitled "Technical Review of On-Line Monitoring Techniques for Performance Assessment." This report includes discussion of both redundant and non-redundant sensor monitoring, the two categories of models involved in on-line monitoring. The second volume of NUREG/CR-6895, which is currently undergoing NRC review, expounds on the general theory of on-line monitoring implementation and the associated uncertainty analysis. Historically used metrics such as accuracy, auto-sensitivity, and cross-sensitivity are used to assess the validity of models developed for online monitoring. Recently, a new fault detectability metric has been developed to evaluate the sensor-fault detection capabilities of these models: Error Uncertainty Limit Monitoring (EULM) detectability [1]. These and other theoretical issues of on-line monitoring have been addressed in previous technical papers and reports [2,3, 4,5,6,7]. However, to help ensure the correct application of on-line monitoring technologies, these techniques should be tested on actual plant data. The third volume of NUREG/CR-6895 is currently under development and will investigate the performance of on-line monitoring (OLM) models under limiting cases in which all of the modeling assumptions may not be met.

This paper presents the results of models developed to monitor three of eleven common nuclear plant sensor sets developed by EPRI during their OLM implementation program [8, 9]. These sensor sets include both redundant sensors sets and non-redundant sensor sets. The Auto-Associative Kernel Regression (AAKR) model architecture is chosen for the analyses. Each of the developed models is evaluated for four metrics: accuracy, auto-sensitivity, cross-sensitivity, and EULM detectability. The analytic and Monte Carlo uncertainty estimates and residual coverage for each model are also calculated. Before the results of these models are discussed, a brief overview of model development and evaluation, the AAKR architecture, and the performance metrics is given.

2. MODEL DEVELOPMENT AND EVALUATION

The model development and analysis for this research were performed using the MATLAB-based Process and Equipment Monitoring (PEM) Toolbox [10], which includes tools for developing and analyzing AAKR models.

Figure 1 outlines the methodology used for model development and analysis. Three data sets are used for model development and evaluation: training data, test data, and validation data. In the first step of this analysis, training data is used for the initial model development. In this step, exemplar observations are chosen from the training data to form a subset of memory vectors; this accounts for all the "training" needed by an AAKR model. The AAKR model architecture is described in more detail in the following section. The second step involves optimizing the model archtecture. This optimization is accomplished using the test data set. The models presented in this research are optimized only for the kernel bandwidth. It is also possible at this stage to optimize a model for the number of memory vectors, the vector selection method, and the distance measure. Finally, the validation data set is used to evaluate the model that was optimized in the previous step. The model is evaluated on four performance metrics: accuracy, auto-sensitivity, cross-sensitivity, and Error Uncertainty Limit Monitoring (EULM) detectability. The model is also analyzed for both analytic and Monte Carlo uncertainty estimates and their corresponding residual coverages [2].

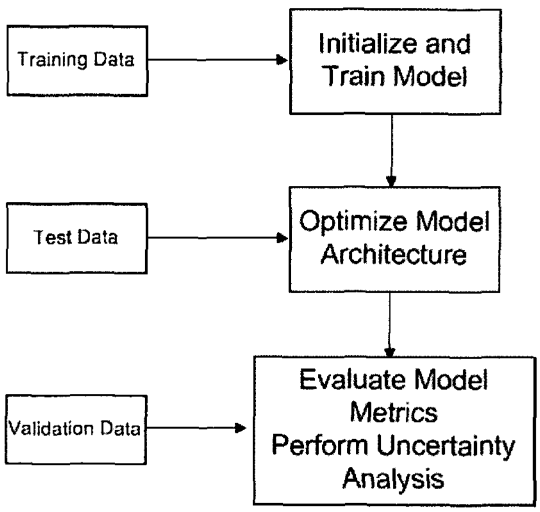


Fig. 1. Methodology for Model Development and Evaluation

2.1 Auto-Associative Kernel Regression

Auto-Associative Kernel Regression (AAKR) is a type of similarity based model [11]. Similarity based modeling (SBM) is a nonparametric modeling technique that uses the similarity of a query vector to memory or exemplar vectors to infer the model's response [12]. The following derivation of the AAKR model architecture is based on multivariate, inferential kernel regression, derived by Wand and Jones [13].

AAKR is a nonparametric, data-driven modeling technique that uses historical, fault-free observations to correct faults in current observations. The exemplar or memory vectors used to develop the empirical model are stored in a matrix $\mathbf{X}_m$ and are selected from a larger training set according to one of many vector selection techniques [5]. Here, each column contains information on a single variable and each row contains one complete observation of all the variables; $X_{i,j}$ is the i^{th} observation of the j^{th} variable. For n_m exemplar observations of p process variables, the memory matrix is written as:

$$\mathbf{X}_m = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,p} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,p} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n_m,1} & X_{n_m,2} & \cdots & X_{n_m,p} \end{bmatrix}$$

Using this format, a query vector is represented by a $1 \times p$ vector of process variable measurements, $\mathbf{x}_q$:

$$\mathbf{x}_q = [x_1 \quad x_2 \quad \cdots \quad x_p]$$

The prediction of the corrected input is calculated as a weighted average of historical, error-free observations termed memory or exemplar vectors ($\mathbf{X}_i$, i=1 to n_m). The AAKR model architecture is composed of three basic steps. First, the distance between a query vector and each of the memory vectors is calculated. There are several distance functions that may be used [3, 14], but the most common measure is the Euclidean distance or L^2-norm. Using this measure, the equation for the distance between the query and the i^{th} memory vector is:

$$d_i(\mathbf{X}_i, \mathbf{x}) = \sqrt{(X_{i,1}-x_1)^2 + (X_{i,2}-x_2)^2 + \cdots + (X_{i,p}-x_p)^2}$$

For a single query vector, this calculation is repeated for each of the n_m memory vectors, resulting in an $n_m \times 1$ matrix of distances: $\mathbf{d}$.

Next, these distances are converted into similarity measures or weights by evaluating the Gaussian kernel:

$$\mathbf{w} = K(\mathbf{d}) = \exp\left(-\frac{\mathbf{d}^2}{h^2}\right)$$

where h is the kernel bandwidth and $\mathbf{w}$ is an $n_m \times 1$ matrix of weights. Other kernel functions can be used but the results are not significantly different.

The prediction of the corrected input is calculated by using these weights to form a weighted average of the memory vectors:

$$\hat{\mathbf{x}} = \frac{\sum_{i=1}^{n_m} (w_i \, \mathbf{X}_i)}{\sum_{i=1}^{n_m} w_i} \qquad (1)$$

It is instructive to note that (1) is simply a modified form of the traditional Nadarya-Watson estimator [15, 16], which weights output exemplars (**Y**) as opposed to input exemplars (**X**).

If the scalar a is defined as the sum of the weights, i.e.

$$a = \sum_{i=1}^{n_m} w_i \,,$$

then (1) can be represented in a more compact matrix notation:

$$\hat{\mathbf{x}} = \frac{\mathbf{w}^T \mathbf{X}}{a}.$$

The parameters to be optimized in an AAKR model are the memory matrix ($\mathbf{X}_m$) and the kernel bandwidth (h). The developer must decide how many and which vectors to include in the memory matrix and how large to make the bandwidth, which indirectly controls how many memory vectors are weighted heavily during prediction. These parameters are problem specific and should be determined independently for each data set.

This section has given a brief description of AAKR. Four metrics and an uncertainty analysis are used to evaluate the performance of SBM. The constituents of this performance evaluation are discussed in the following section.

2.2 Performance Metrics

Each model presented in this paper is evaluated with a set of performance metrics and an uncertainty analysis. The results for each model of these analyses are presented in tables. Short definitions are given below for the performance metrics given in the model results tables of the following sections. These definitions are grouped according to the table sections shown in Table 1.

Accuracy measures how well a model predicts the correct values for new inputs. It is characterized by the root mean-squared error, given as percent of sensor span.

Table 1. Categories of Model Performance Evaluation

Metrics:	Accuracy (% of span)
	Auto-Sensitivity
	Cross-Sensitivity
	EULM Detectability (%)
Uncertainty:	Analytic (% of span)
	Coverage
	Monte Carlo (% of span)
	Coverage

The accuracy of the k[th] sensor is given by:

$$A_k = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{x}_{k_i} - x_{k_i}\right)^2}}{s_k} \times 100\%$$

where s_k is the span of the k[th] sensor.

While accuracy metrics may be sufficient for models that are expected to operate with correct inputs, calibration verification models are explicitly designed to detect sensor faults, and thus must operate with faulty inputs. Sensitivity metrics characterize the effect of drifted sensor inputs on the model output. Two such metrics are used to evaluate model performance, namely auto-sensitivity and cross-sensitivity [5]. Ideally, these sensitivity metrics should be valued between 0.0 and 1.0. Sensitivity values greater than 1.0 indicate that a model is actually amplifying the effect of an input sensor drift.

Auto-Sensitivity measures how a faulted variable input affects predictions for that same variable. It quantifies how much a sensor prediction follows a sensor drift. The auto-sensitivity of the k[th] sensor is given by:

$$S_{A_k} = \frac{\sum_{i=1}^{n}\left|\hat{x}_{ki}^{drift} - \hat{x}_{ki}\right|}{\sum_{i=1}^{n}\left|x_{ki}^{drift} - x_{ki}\right|}$$

Cross-Sensitivity measures how a faulted variable input affects predictions for the other variables. The cross-sensitivity of the j[th] sensor due to a drift in the k[th] sensor is given by:

$$S_{C_{j,k}} = \frac{\sum_{i=1}^{n}\left|\hat{x}_{ji}^{drift} - \hat{x}_{ji}\right|}{\sum_{i=1}^{n}\left|x_{ki}^{drift} - x_{ki}\right|}$$

The overall sensor cross-sensitivity is given by the average of the cross-sensitivity due to a drift in each of the other sensors:

$$S_{C_j} = \frac{\sum_{\substack{k=1 \\ k \neq j}}^{N} S_{C_{j,k}}}{N-1}$$

A newly developed fault detectability metric is also used to evaluate model performance: EULM detectability. **EULM Detectability** indicates the smallest sensor fault that can be detected by an empirical model with a 95% confidence and is reported as a percent of the sensor span. The utility of the EULM detectability is that, while the accuracy and sensitivity metrics provide some guidance, they do not give concrete guidance on the smallest faults that can be detected by monitoring the uncertainty of the prediction residuals. The EULM detectability for the i^{th} sensor is given by:

$$D_{EULM\,i} = \frac{U_i / s_i}{\left(1 - S_{A\,i}\right)}$$

where U_i is the uncertainty in the i^{th} sensor and s_i is its span. Past measures of detectability consider only the predictive uncertainty. A sensor would have to drift more than the 95% uncertainty value for one to be confident that the drift occurred and that it was not just a prediction error. These earlier methods did not consider auto-sensitivity. Recall that auto-sensitivity causes a residual to be smaller than an actual drift because the prediction will somewhat follow the drift. EULM takes this into consideration and scales the earlier detectability measure accordingly. For example, if a sensor drifts by 1% and the auto-sensitivity is 0.5, the residual would only be 0.5% rather than the necessary 1%. Dividing by $1-S_A$ corrects for predictions that have a tendency to follow drifts. With the auto-sensitivity correction factor, EULM detectability would result in a 1% residual when the drift is 1%. The uncertainty term used in the EULM detectability metric will now be discussed.

2.3 Uncertainty

The analytic and Monte Carlo methods for calculating uncertainty are described in NUREG/CR-6895, Volume II. Analytic uncertainty is estimated through equations derived from the model's mathematical architecture. Analytic uncertainty can be evaluated during model implementation to estimate the uncertainty for each prediction. The Monte Carlo uncertainty, however, is much more computationally intensive. As such, it is generally evaluated prior to model implementation. This uncertainty estimate is applied to each model prediction. Monte Carlo uncertainty is estimated by applying a Monte Carlo re-sampling technique. With Monte Carlo techniques, the training data is resampled multiple times and for each of these resampled datasets, a new model is constructed. The variation between all of these models is then taken as a measure of the variance portion of the total uncertainty. Because the Monte Carlo methods measure the uncertainty of many possible models, instead of only the model at hand, their uncertainty estimates are generally larger than analytic estimates. However, research has shown that both analytic and Monte Carlo techniques generally provide a conservative estimate of model uncertainty [17]. The uncertainty estimate is applied to the denoised residuals of the model. This uncertainty is used to construct a confidence interval centered at zero, the expected value of the denoised residuals. The residual coverage is then calculated as the fraction of denoised residuals contained within the confidence interval.

3. DATA SETS

This report presents the results of models generated with three different sensor sets: Pressurizer Level, Reactor Protection System (RPS) Loop A, and Reactor Coolant System (RCS) Loop A Steam Generator (SG) Level. RPS Loop A and RCS Loop A SG Level contain non-redundant groups of redundant sensors. The Pressurizer Level sensor set contains only redundant sensors. These models are described in the EPRI document "On-Line Monitoring of Instrument Channel Performance Volume 2" [8]. Data was collected for each sensor as well as the reactor power level from March 2001 to November 2002 with a one-minute sampling rate for all sensors. The reactor power level data was used as a phase indicator; the models presented here include only high-power data, power greater than 960 MWe. This high-power data was separated into three data sets for each model evaluation. The training set includes data from March, April, and May, 2001 with a five-minute sampling rate; the test data set includes data from March 2001 through April 2002 with a fifteen-minute sampling rate; the validation data set includes data similar to the test data set, but offset by seven minutes.

3.1 Pressurizer Level

The Pressurizer Level sensor set contains three redundant level sensors. Figure 2 shows the training and test data used to develop the AAKR model. In this and all other data sets, the validation data is similar to the test data and is not presented. Table 2 gives the noise estimates of each sensor and the correlation coefficients for the training data set. As the table shows, the sensor training data is highly correlated, above 0.95. The performance evaluation of this model is summarized in Section 4.

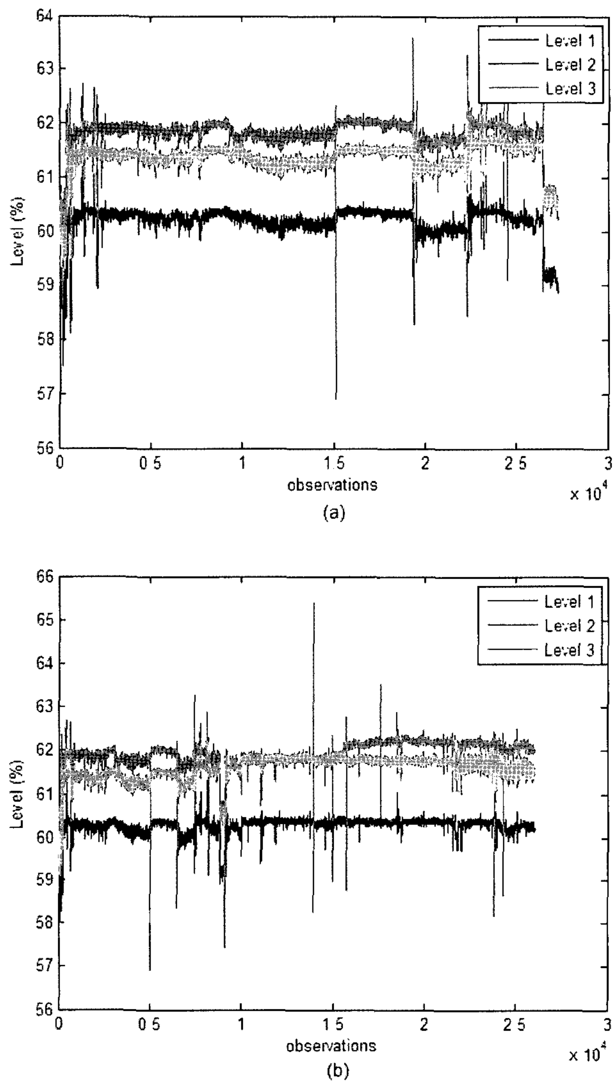


Fig. 2. (a) Training and (b) Test Data for the Pressurizer Level *Model*

Table 2. Pressurizer Level Noise Estimates and Correlation Coefficients

	Level 1	Level 2	Level 3
Signal Noise Estimate (% of span)	0.051	0.051	0.052
Correlation Coefficients			
Level 1	1.000	0.988	0.965
Level 2	0.988	1.000	0.952
Level 3	0.965	0.952	1.000

3.2 RPS Loop A

The RPS Loop A sensor set contains nine sensors in four redundant groups. Figure 3 shows the training and test data used to develop the AAKR model. Table 3 gives the noise estimates of each sensor and the correlation coefficients for the training data set. As the table shows, the sensor training data is highly correlated within the redundant sets with most of these correlations above 0.95. The exception to this is the steam flow sensors. The correlation of these sensors is somewhat degraded; however, this is attributed to the high level of noise common in steam flow sensors. It is also clear that the feedwater flow, steam flow, and first stage turbine pressure are all inter-correlated. The three steam pressure sensors, however, are not significantly correlated with any other sensor set. The performance evaluation of this model is summarized in Section 4.

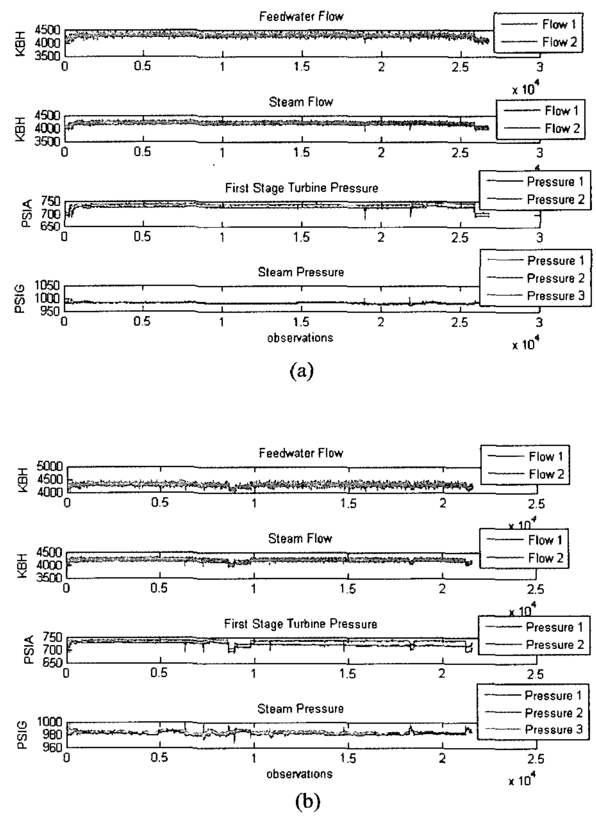


Fig. 3. (a) Training and (b) Test Data for RPS Loop A Model

3.3 RCS Loop A SG Level

The RCS Loop A SG Level sensor set contains four SG level sensors: three narrow range level sensors and one wide range level sensor. Figure 4 shows the training and test data used to develop the AAKR model. Table 4 gives the noise estimates of each sensor and the correlation coefficients for the training data set. The correlation coefficients of the three narrow range level sensors are all high, above 0.97. However, the wide range sensor is not significantly correlated with any of the narrow range sensors. The performance evaluation of this model is summarized in Section 4.

4. MODEL RESULTS

Three AAKR models were developed using each of the data sets described. The models were developed using the training data and evaluated using the test or validation data. The results for each sensor in each model are summarized below.

Metrics of particular interest include accuracy, EULM detectability, and the estimates of uncertainty. For OLM implementation, it is generally agreed that these three measures must be less than 1% of the sensor span to be usable. This is because it is common to have allowable drift levels between calibration intervals on that order of magnitude. An EULM detectability of above 1% makes it impossible to detect a drift of 1% with a 95% confidence. A 95% confidence is required because that is the confidence necessary for safety critical nuclear instrumentation calibrations.

Accuracy is a measure of how well the model predicts with unfaulted input data. However, since it reflects the error between the prediction and target, it may be overly inflated due to sensor noise. If the predictions were perfect and the sensor had instrumentation noise, the error would be equal to that noise level. Therefore, it is not practical to have an error less than the noise level.

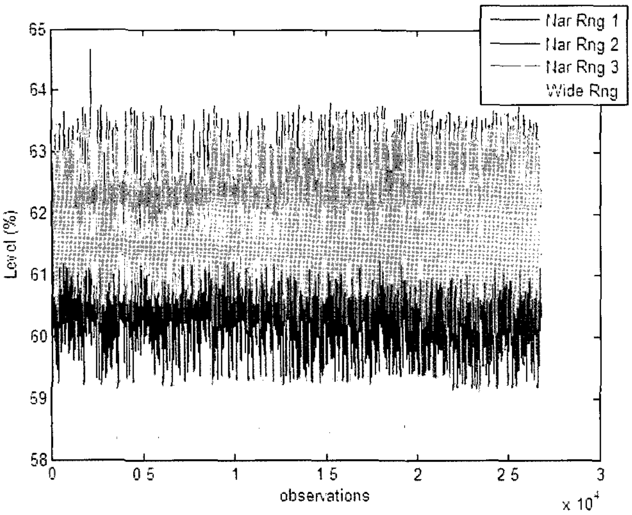
Table 3. RPS Loop A Noise Estimates and Correlation Coefficients

	FWF1	FWF 2	SF 1	SF 2	TP 1	TP 2	SP 1	SP 2	SP 3
Signal Noise Estimate (%)	0.561	0.543	0.607	0.607	0.035	0.035	0.023	0.022	0.029
Correlation Coefficients									
FWF1	1.000	0.968	0.690	0.689	0.811	0.794	-0.122	-0.110	-0.172
FWF 2	0.968	1.000	0.688	0.686	0.809	0.789	-0.100	-0.081	-0.154
SF 1	0.690	0.688	1.000	0.647	0.774	0.758	-0.193	-0.171	-0.229
SF 2	0.689	0.686	0.647	1.000	0.775	0.758	-0.186	-0.167	-0.273
TP 1	0.811	0.809	0.774	0.775	1.000	0.991	-0.102	-0.082	-0.126
TP 2	0.794	0.789	0.758	0.758	0.991	1.000	-0.133	-0.124	-0.148
SP 1	-0.122	-0.100	-0.193	-0.186	-0.102	-0.133	1.000	0.968	0.951
SP 2	-0.110	-0.081	-0.171	-0.167	-0.082	-0.124	0.968	1.000	0.953
SP 3	-0.172	-0.154	-0.229	-0.273	-0.126	-0.148	0.951	0.953	1.000

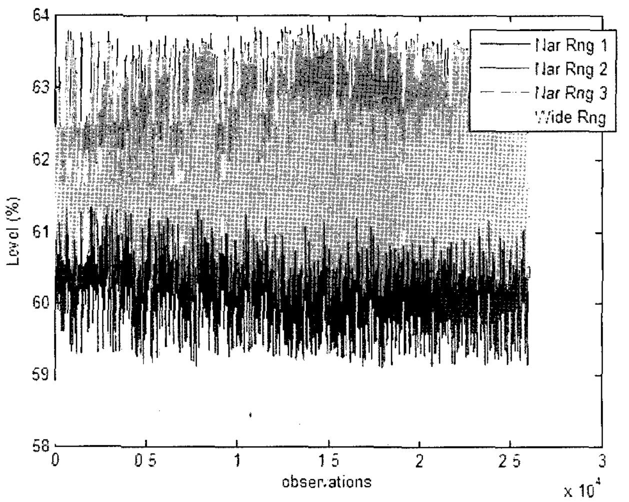
* FWF : Feedwater Flow, SF: Steam Flow, TP : First Stage Turbine Pressure, SP: Steam Pressure

Table 4. RCS Loop A SG Level Noise Estimates and Correlation Coefficients

	NAR RNG 1	NAR RNG 2	NAR RNG 3	WIDE RNG
Signal Noise Estimate (%)	0.337	0.323	0.328	0.259
Correlation Coefficients				
NAR RNG 1	1.000	0.973	0.986	0.142
NAR RNG 2	0.973	1.000	0.983	0.183
NAR RNG 3	0.986	0.983	1.000	0.157
WIDE RNG	0.142	0.183	0.157	1.000



(a)



(b)

Fig. 4. (a) Training and (b) Test Data for RCS Loop A SG Level Model

Table 5. Results of Pressurizer Level Model

	Level 1	Level 2	Level 3
Metrics:			
Accuracy (% of span)	0.076	0.110	0.073
Auto-Sensitivity	0.427	0.519	0.505
Cross-Sensitivity	0.221	0.272	0.233
EULM Detectability (% of span)	0.249	0.448	0.278
Uncertainty Analysis:			
Analytic (% of span)	0.143	0.215	0.137
Coverage	0.976	0.993	0.951
Monte Carlo (% of span)	0.127	0.205	0.122
Coverage	0.958	0.989	0.948

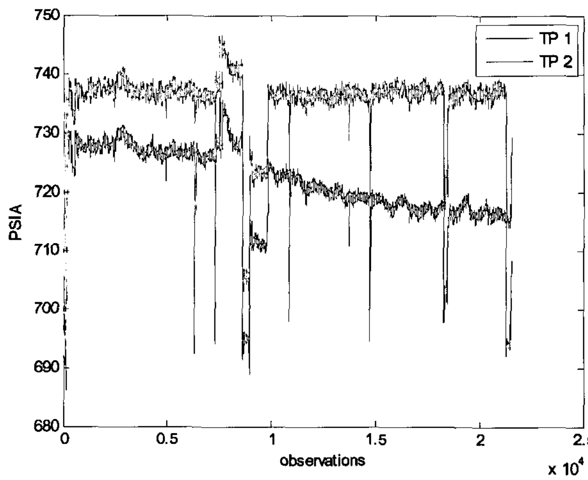


Fig. 5. First Stage Turbine Pressure Sensors in the Validation Data Range

4.1 Pressurizer Level

The results of a performance evaluation of the Pressurizer Level model are summarized in Table 5. The performance metrics for this model are very good. Both accuracy and uncertainty are well below the desired 1% level. The EULM detectability indicates that the model can detect drifts of less than 0.5% of the sensor span. This model should be considered acceptable for implementation in an OLM system.

4.2 RPS Loop A

The results of the performance evaluation of the RPS Loop A model are summarized in Table 6. The results of this model show that the accuracy indicator is well within the 1% guideline. However, the uncertainty for several sensors is above that level, as is the EULM detectability. In fact, this model cannot detect sensor drifts of less than 2.5% for several of the sensors. These unfavorable results motivate a closer look at the data used for model development and analysis.

Two methods are readily apparent for investigating the data sets: correlation analysis and visual inspection. A correlation analysis of the validation data (Table 7) shows that the correlation between the two first stage turbine pressure (TP) sensors has degraded significantly, from 0.99 in the training data to 0.80 in the validation data. The correlation of TP 1 to the other, non-redundant sensors has also degraded. This indicates that perhaps a fault is present in this sensor. A plot of the two first stage turbine pressure sensors is given in Figure 5. This figure shows a very clear drift in TP 1, which is likely the cause of the poor model performance seen above.This clearly illustrates the importance of data inspection before model development. Had this been an in-use OLM model coupled with a detection system, the sensor drift could have been detected and the instrument scheduled for maintenance.

4.3 RCS Loop A SG Level

The results of the RCS Loop A SG Level model are summarized in Table 8. The results of this model show that the accuracy indicator and the uncertainty for each sensor are well within the 1% guideline. In addition, the EULM detectabilities for the three narrow range level sensors indicate that a ~0.6% drift of the sensor span could be detected with this model. The EULM detectability for the wide range level sensor, however, is much higher than the desired 1%. Since the uncertainty is similar to that of the narrow range instruments, the poor EULM detectability is due to the poor auto-sensitivity.

Table 6. Results of RPS Loop A Model

	FWF1	FWF 2	SF 1	SF 2	TP 1	TP 2	SP 1	SP 2	SP 3
Metrics:									
Accuracy (% of span)	0.316	0.308	0.342	0.314	0.805	0.246	0.055	0.051	0.056
Auto-Sensitivity	0.377	0.434	0.592	0.581	0.221	0.163	0.416	0.428	0.340
Cross-Sensitivity	0.126	0.124	0.120	0.121	0.077	0.087	0.151	0.172	0.160
EULM Detectability (% of span)	1.600	1.710	2.600	2.530	2.070	0.588	0.187	0.176	0.168
Uncertainty Analysis:									
Analytic (% of span)	0.996	0.970	1.060	1.060	1.610	0.492	0.109	0.101	0.111
Coverage	0.990	0.990	0.991	0.997	0.995	0.946	0.973	0.981	0.972
Monte Carlo (% of span)	0.903	0.843	0.947	1.010	1.810	0.907	0.185	0.197	0.193
Coverage	0.989	0.989	0.988	0.996	0.996	0.985	0.991	0.996	0.994

FWF: Feedwater Flow, SF: Steam Flow, TP: First Stage Turbine Pressure, SP: Steam Pressure

Table 7. Correlation Coefficents of RPS Loop A Test Data

	FWF1	FWF 2	SF 1	SF 2	TP 1	TP 2	SP 1	SP 2	SP 3
FWF1	1.000	0.963	0.610	0.612	0.526	0.725	-0.344	-0.348	-0.367
FWF 2	0.963	1.000	0.607	0.608	0.534	0.726	-0.325	-0.323	-0.361
SF 1	0.610	0.607	1.000	0.598	0.524	0.738	-0.397	-0.399	-0.412
SF 2	0.612	0.608	0.598	1.000	0.529	0.744	-0.399	-0.401	-0.465
TP 1	0.526	0.534	0.524	0.529	1.000	0.805	-0.320	-0.189	-0.248
TP 2	0.725	0.726	0.738	0.744	0.805	1.000	-0.404	-0.378	-0.415
SP 1	-0.344	-0.325	-0.397	-0.399	-0.320	-0.404	1.000	0.960	0.915
SP 2	-0.348	-0.323	-0.399	-0.401	-0.189	-0.378	0.960	1.000	0.935
SP 3	-0.367	-0.361	-0.412	-0.465	-0.248	-0.415	0.915	0.935	1.000

FWF: Feedwater Flow, SF: Steam Flow, TP: First Stage Turbine Pressure, SP: Steam Pressure

Table 8. Results of RCS Loop A SG Level Model

	NAR RNG 1	NAR RNG 2	NAR RNG 3	WIDE RNG
Metrics:				
Accuracy (% of span)	0.051	0.078	0.067	0.057
Auto-Sensitivity	0.324	0.338	0.292	0.857
Cross-Sensitivity	0.188	0.186	0.185	0.065
EULM Detectability (% of span)	0.584	0.590	0.552	2.070
Uncertainty Analysis:				
Analytic (% of span)	0.395	0.391	0.391	0.296
Coverage	1.000	1.000	1.000	1.000
Monte Carlo (% of span)	0.154	0.149	0.147	0.198
Coverage	1.000	0.977	0.999	1.000

Recall that the correlation of the wide range sensor to the three narrow range sensors was quite low (< 0.2). This is probably due to the water level controller minimizing variable fluctuations and thus minimizing the sensor correlations. The narrow range instruments' process noise has higher correlations than with the wide range sensor due to the sensor leg penetration locations. Therefore, no sensor was included in this model, which was truly redundant with a wide range level. This illustrates the importance of signal selection in model development. The RPS Loop A data also contained sensors that were not highly correlated with the other sensor groups; however, the model performance on these sensors was quite high. This is due, in part, to their redundancy within the group. When selecting signals for model development, it is important that each signal be well correlated with the other signals [8]. It is also suggested that each signal have at least one redundancy included in the model.

5. CONCLUSIONS

This paper presented the results of model development and analysis for three nuclear plant sensor sets. One model, the Pressurizer Level model, had acceptable performance for OLM. The other two models, RPS Loop A and RCS Loop A SG Level, highlighted two problems commonly encountered in model development. The RPS Loop A model was tested using data with a sensor drift fault, which resulted in poor model measured performance. In an applied OLM system, a correctly trained model, coupled with a fault detection routine, would have identified the sensor drift in the first stage turbine pressure signal. Finally, the RCS Loop A SG Level model contained a sensor that was not highly correlated with the other three sensors. This model had very good performance on the three redundant sensors, but its ability to detect drifts in the non-redundant sensor was significantly degraded. This illustrates the importance of signal selection in developing models for OLM systems.

It is important to note that the purpose of this study was to implement OLM using actual nuclear plant data and methods that have been proposed by EPRI and others. It was not to identify deficiencies in the described OLM methods, but to investigate how the methods fail when using actual data that may not meet all of the underlying assumptions. If OLM is to be used in operating nuclear power plants, the ways in which the results change for common data and model development problems must be well understood.

This paper presents the results of the first academic implementation of OLM for sensor calibration monitoring and an analysis of the underlying causes of the performance deficiencies. It investigated actual data problems. A study of simulated problems that could possibly cause model performance deficiencies is included in the third volume of NUREG/CR-6895, which is expected to be published in 2007.

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