Phase II+ Final Report

Volume I

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On-Line Monitoring of Accuracy and Reliability of Instrumentation and Health of Nuclear Power Plants

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PREFACE

This is Volume I of a two-volume report written by Analysis and Measurement Services Corporation (AMS) for the U.S. Department of Energy (DOE) to present the results of a comprehensive research and development (R&D) project aimed at development, validation and implementation of On-Line Monitoring (OLM) technologies for equipment and plant health assessment. This volume describes the project objectives and discusses the main results, and Volume II includes the supporting information and data. For simplicity, the table of contents for both Volume I and Volume II are included in each volume.

This project began in 2006 with a Phase I effort and continued on from 2007 to 2011 in Phase II and subsequently as a Phase II+ (Phase two plus). The report herein concludes the work of the Phase II+ project.

NUCLEAR INDUSTRY CONTRIBUTORS

The successful completion of the Phase II+ project described in this report was facilitated by the active participation of a number of nuclear industry professionals. In particular, the contributions of the following individuals are gratefully acknowledged:

Alan Dowell	Dominion
Michael Eidson	Southern Nuclear Operating Company
Raymond Herb	Southern Nuclear Operating Company
Jerry Hubbell	Dominion
Otis Seals	Southern Nuclear Operating Company
Kevin Tate	Southern Nuclear Operating Company

In addition, AMS appreciates the contributions of the instrumentation and control (I&C) personnel at the Farley and North Anna nuclear power stations who provided data, access to plant equipment, and help in many other aspects of the project.

Finally, AMS would like to thank the DOE project manager, Dr. Madeline Feltus, for her technical advice, constructive criticism, and effective oversight of this project.

EXECUTIVE SUMMARY

This report concludes a three phase project that was performed over a period between June 2006 and June 2011. The project was broken up into three phases called Phase I (June 2006 to March 2007), Phase II (August 2007 to August 2009) and Phase II+ (August 2009 to June 2011). Collectively, this project involved development, validation, and implementation of On-Line Monitoring (OLM) technology for equipment and process health monitoring in nuclear power plants. The project focused on Instrumentation and Control (I&C) Systems of nuclear power plants, although other plant equipment can also benefit from the OLM development presented here. The OLM development on I&C Systems performed under the three phases here included static and dynamic performance verification of process instrumentation and systems as well as detection of anomalies in the process using signals from existing I&C equipment. For implementation, four U.S. nuclear power plants were used as the test bed. These were the two units at Farley Nuclear Power Plant in Alabama which are Westinghouse 3-loop PWRs and the two units at North Anna Nuclear Power Plant in Virginia which are also Westinghouse 3-loop PWRs.

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ABBREVIATIONS/ACRONYMS

AAKR	Auto Associative Kernel Regression
AC	Alternating Current
A/D	Analog-to-Digital
APD	Amplitude Probability Density
AMS	Analysis and Measurement Services Corporation
ANL	Argonne National Laboratory
AR	Autoregressive
ARMA	Autoregressive Moving Average
BE	British Energy
BOP	Balance-of-Plant
BWR	Boiling Water Reactor
C-E	Combustion Engineering
CDs	Compact Discs
CIP	Critical Infrastructure Protection
CRP	Coordinated Research Project
CRS	Calibration Reduction System
DC	Direct Current
DOE	Department of Energy
DS&S	Data Systems and Solutions
EPRI	Electric Power Research Institute
FPGA	Field Programmable Gate Array
FTP	File Transfer Protocol
Hz	Hertz
HRP	Halden Reactor Project
I&C	Instrumentation and Control
IAEA	International Atomic Energy Agency
ICA	Independent Component Analysis
ICMP	Instrument Calibration and Monitoring Program
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
INL	Idaho National Laboratory
IT	Information Technology

LAN	Local Area Network
MDL	Minimum Descriptive Length
MSET	Multivariate State Estimation Technique
NERC	North American Electric Reliability Corporation
NI	National Instruments
NNPLS	Neural Network Partial Least Squares
NPPs	Nuclear Power Plants
NRC	U.S. Nuclear Regulatory Commission
OLM	On-Line Monitoring
PC	Personal Computer
PCA	Principal Component Analysis
PEANO	Process Evaluation and Analysis by Neural Operators
PEM	Process and Equipment Monitoring
PLS	Partial Least Squares
PMAX	Performance Maximization
PNNL	Pacific Northwest National Laboratory
PRA	Probabilistic Risk Analysis
PSD	Power Spectral Density
PWR	Pressurized Water Reactor
PWROG	Pressurized Water Reactors Owners Group
QA	Quality Assurance
R&D	Research and Development
RCS	Reactor Coolant System
RIO	Reconfigurable Input/Output
RTD	Resistance Temperature Detector
SAIC	Science Applications International Corporation
SBIR	Small Business Innovation Research
SDP	Surveillance, Diagnostics, and Prognostics
SER	Safety Evaluation Report
SG	Steam Generator
SNOC	Southern Nuclear Operating Company
TCP/IP	Transmission Control Protocol/Internet Protocol
TEMPO	Thermal Performance Monitoring and Optimization
UT	University of Tennessee

1. INTRODUCTION

1.1 Background

This report describes the work performed by Analysis and Measurement Services Corporation (AMS) under a multi-phase Small Business Innovation Research (SBIR) grant entitled 'On-Line Monitoring of Accuracy and Reliability of Instrumentation and Health of Nuclear Power Plants' that was awarded by the U.S. Department of Energy (DOE). The primary goal of the work was to design and develop an integrated on-line monitoring (OLM) system and demonstrate its use in operating nuclear power plants. The project spanned over 5 years, beginning with the award of the Phase I project in 2006, followed by the Phase II project in 2007, and the Phase II+ project in August 2009. Table 1.1 below provides a summary of each of these projects, along with a description of the primary goals of each one. Detailed descriptions of the accomplishments of each of the projects listed in Table 1.1 are provided in Section 1.4 of this report.

Table 1.1 SBIR Project Summaries

Item	Project	Time Period	Primary Goal
1	Phase I	June 2006 – March 2007	Establish the feasibility of implementing OLM for accuracy and reliability of instrumentation and health of nuclear power plants.
2	Phase II	August 2007 – August 2009	Design and develop an OLM system and demonstrate its use in a nuclear power plant.
3	Phase II+	August 2009 – June 2011	Expand the work of the Phase II effort to apply OLM techniques to four U.S. nuclear power plants.

As shown in Table 1.1, the primary goal of the Phase II+ project was to expand the work performed during the Phase II project to include OLM analysis for a total of 4 U.S. nuclear reactors, namely Farley Units 1 and 2 (owned by Southern Nuclear Operating Company) and North Anna Units 1 and 2 (owned by Dominion). All four reactors are three-loop Westinghouse Pressurized Water Reactors (PWRs).

The work described herein builds upon the research and development (R&D) performed during the previous Phase I and Phase II projects that are documented in Phase I [1] and Phase II [2] reports, respectively. This report focuses instead on presenting the OLM results for the four reactors evaluated during this project. However, the appendices of this report provide background information on the concept of OLM (Appendix A), details of various OLM analysis techniques (Appendices B, C, and D), and a description of the OLM system used to produce the results for this report (Appendix E). Where appropriate, sections of the Phase I and Phase II reports are included in this report for simplicity.

1.2 Description of the SBIR Program

The SBIR program is designed by the U.S. government to stimulate innovation in the private sector and is provided to small businesses (for example, companies that have less than 500 employees or meet other qualifying criteria as determined by the U.S. Small Business Administration) on a competitive basis. To obtain an SBIR grant from the DOE, a proposal must be submitted for a Phase I project in response to a solicitation that the DOE publishes annually. If approved, the proposing firm is provided with up to $100,000 in funds and must demonstrate the feasibility of its proposed innovation over a 9-month period. Upon successful completion of the Phase I project, proposing firms are encouraged to submit a Phase II proposal, which is also evaluated on a competitive basis. If successful, a Phase II grant is awarded to the proposing firm with funds of up to $750,000 and two years to complete the Phase II project. Depending on the success of the Phase II project and the availability of resources from the DOE, Phase II projects may qualify for supplemental funding of up to $250,000 to extend the Phase II project for a period of one year. To qualify for Phase II+ funding, grantees must have satisfactorily completed at least 1 year of their Phase II research project, and must be formally invited by their DOE Project Officer to submit a request for supplemental funds. There are two types of Phase II+ funding requests that are acceptable to the DOE:

1. **Type 1** – If the grantee is requesting financial support for a new task or activity to be added to the original Phase II grant
2. **Type 2** – If the grantee needs additional funds to increase the level of effort with no change to the Phase II project description

Analysis and Measurement Services Corporation (AMS) was successful in winning a Phase I grant in 2006, a Phase II grant in 2007, and a Type 2 Phase II+ grant in 2009 for this project.

This report provides the details of the work that AMS performed under the Phase II+ project. Additional information regarding the Phase I and Phase II projects are provided in separate reports that were produced by AMS for the DOE at the conclusion of each project.

1.3 Project Objective

The primary objective of the Phase II project was to design and develop an integrated on-line monitoring (OLM) system and demonstrate its use in an operating nuclear power plant. To this end, AMS developed a system which combined new software and hardware designs to provide a comprehensive framework for performing both static and dynamic OLM analysis. In addition, the system was demonstrated using operating nuclear power plant data [2]. Although several U.S. utilities expressed interest in becoming a test bed for the OLM system developed under the Phase II effort, the original project scope provided time and resources for demonstrating OLM analysis for only one U.S. reactor (the Farley Nuclear Power Station Unit 1, a Westinghouse three-loop PWR in Alabama owned by Southern Nuclear Operating Company).

The project reported herein (reported as Phase II+) increased the level of effort of the Phase II project to demonstrate OLM analysis for transmitter health monitoring in three additional nuclear reactors, namely, Farley Unit 2, and North Anna Units 1 & 2. Demonstrating OLM analysis for Farley Units 1 and 2 and North Anna Units 1 and 2 involved the following technical tasks:

- Acquiring suitable OLM data
- Developing OLM models
- Performing OLM analysis
- Documenting the OLM results

The OLM analysis for the four reactors involved data from over 500 sensors (combined) for a period of time including 9 operating cycles. The OLM data acquired for this project represents one of the largest repositories of nuclear power plant OLM data that has been analyzed to date. The results of the OLM analysis performed for this project demonstrate that the majority of transmitters do not exhibit drift over a typical fuel cycle. The results also demonstrate that OLM is an effective tool for performance monitoring of nuclear power plant instrumentation during plant operation. Details of the OLM analysis for each of the four reactors are provided in this report in the main body and in the appendices of Volume II of this report.

In addition to completing the above technical tasks for each reactor, the Phase II+ effort also involved using the OLM analysis results to support the Pressurized Water Reactor Owner's

Group (PWROG) effort to compile the technical bases and methods to justify transmitter calibration interval extension. Details regarding the PWROG effort and AMS' participation in the project are also provided in this report.

AMS has worked over the last three years (using its own funds) to commercialize the product of this project. This effort has been successful in bringing commercial revenue to AMS from the nuclear industry. Furthermore, AMS has shared the results of this R&D with the worldwide nuclear community through participation, sponsorship, and hosting of several national and international meetings with nuclear industry personnel to explain the capabilities and benefits of the OLM system developed as part of this project.

1.4 Project Summaries

This section provides a detailed summary of the accomplishments of the Phase I, Phase II, and Phase II+ projects that were performed under DOE Grant Number DE-FG02-06ER84626 from June 2006 to June 2011.

1.4.1 Phase I Summary

As previously stated, the goal of the Phase I project was to establish the feasibility of an OLM system that can be readily implemented in nuclear power plants to reduce hands-on maintenance of process instrumentation, assess the accuracy and reliability of critical measurements, and provide plant-wide diagnostics.

The goal of the Phase I project was successfully reached by execution of the following objectives over a nine-month period from June 2006 to March 2007:

1. Identify Sources of Plant Data
2. Evaluate Means for Data Acquisition
3. Identify Data Qualification Means
4. Identify Data Analysis Techniques
5. Create a Conceptual OLM System Design

Table 1.2 summarizes the key accomplishments of the Phase I project in terms of the objectives listed above. Details on how these objectives were met can be found in the sections that follow.

A more comprehensive overview of the Phase I accomplishments can be found in the Phase I final report [1].

1.4.2 Phase II Summary

The primary goal of the Phase II project was to construct an OLM system and demonstrate its use in a nuclear power plant. This primary objective was to be realized by completing seven technical objectives as listed below:

1. Develop an Integrated OLM System Architecture from the Conceptual Phase I Design
2. Develop Software/Hardware Modules for the OLM System
3. Develop Analytical Models and Other Parameters for Selected Plant Processes
4. Validate the OLM System with a Test Loop
5. Implement and Demonstrate the OLM System in an NPP
6. Design the Commercial Prototype
7. Provide the Design of an Embedded OLM System for Next Generation Reactors

Table 1.3 summarizes the key accomplishments of the Phase II project in terms of the seven technical objectives. More detailed information about the OLM system design and other Phase II technical objectives are found in the Phase II report [2].

Table 1.2 Summary of Phase I Accomplishments

Technical Objectives of Phase I Project	Phase I Accomplishments
1. Identify Sources of Plant Data	Nuclear power plant data was obtained and used for evaluation of analysis techniques in Phase I. In addition, contacts were made with eighteen nuclear power plants (seventeen domestic and one foreign) to determine the means and procedures that must be established for OLM data acquisition from nuclear power plants.
2. Evaluate Means for Data Acquisition	A data acquisition system was designed to take data at sampling rates sufficient for dynamic analysis.
3. Identify Data Qualification Means	A number of existing statistical algorithms were identified and tested using nuclear power plant data to establish their feasibility for screening, cleanup, and preprocessing of OLM data.
4. Identify Data Analysis Techniques	For static data analysis, the Kernel Regression algorithm was identified from a variety of available methods that were evaluated for process modeling of nuclear plant data. For dynamic data analysis, several Autoregressive (AR) modeling algorithms were evaluated including Yule-Walker, Burg, Covariance, and Modified Covariance. Also, several AR optimum model order methods were evaluated. It was determined that no one method is best for every case; therefore, all of these methods should be implemented in the OLM system.
5. Create a Conceptual OLM System Design	A conceptual OLM system was designed to integrate the techniques evaluated in this project. The OLM system integrates two sets of existing techniques into one system. That is, the noise analysis technique for dynamic data analysis and the process modeling technique for static analysis.

Table 1.3 Summary of Phase II Accomplishments

	Technical Objectives of Phase II Project	Phase II Accomplishments
1.	Develop Integrated OLM System Architecture from Phase I Design	Created a modular system design with interfaces that can be controlled remotely and a software architecture that facilitates seamless inclusion of additional analysis modules.
2.	Develop Software/Hardware Modules for the Integrated OLM System	Developed data acquisition, data qualification and cleaning, data analysis, and database software modules. Developed a 24-bit data acquisition system for high-speed data collection.
3.	Develop Analytical Model and Other Parameters for Selected Plant Processes	Developed kernel regression models for Reactor Coolant System, Pressurizer, and Steam Generator for a 3-loop PWR. Developed optimal dynamic analysis parameters for several pressure, level, and flow transmitters.
4.	Validate the Prototype OLM System with a Test Loop and Plant Data	Validated the OLM system hardware and software modules with data taken from the AMS test loop and with data taken in operating NPPs.
5.	Implement and Demonstrate the Prototype OLM System in an NPP	Implemented and demonstrated the prototype OLM system at the Farley Unit 1 NPP.
6.	Design the Commercial Prototype	Produced the design of the commercial OLM system based on the prototype developed in Phase II.
7.	Provide the Design of an Embedded OLM System for Next Generation Reactors	Reviewed the available Instrumentation and Control (I&C) designs of next generation reactors and established the parameters for embedding an OLM system in the design.

1.4.3 Phase II+ Summary

The purpose of the Phase II+ project was to extend the work of the Phase II effort to include OLM analysis of four U.S. nuclear reactors and provide support to the Pressurized Water Reactor Owners Group (PWROG) in establishing a generic licensing path for using OLM tools to help extend transmitter calibration intervals. These goals were to be realized by completing four technical objectives as listed below:

1. Develop Analytical Models for OLM
2. Demonstrate OLM Analysis in four NPPs
3. Document the OLM Analysis Results
4. Support PWROG Efforts on Generic Licensing of OLM

Table 1.4 summarizes the key accomplishments of the Phase II+ project in terms of the four technical objectives. More detailed information about the OLM results and the PWROG generic licensing effort can be found in later sections of this report.

Table 1.4 Summary of Phase II+ Accomplishments

Technical Objectives of Phase II+ Project	**Phase II+ Accomplishments**
1. Develop Analytical Models for OLM	Developed analytical models for each of the four reactors evaluated during this project. Analytical models were developed for Steam Generator Loops, Pressurizer, and Reactor Coolant System Loops which encompass 50+ transmitters in each reactor.
2. Demonstrate OLM Analysis in four NPPs	Performed OLM analysis for each of the four reactors spanning over 9 operating cycles combined. OLM analysis included data qualification, redundant sensor analysis, analytical modeling analysis, and dynamic analysis.
3. Document the OLM Analysis Results	Summaries of the OLM analysis for each reactor are documented in this report. Detailed analysis plots for each reactor are provided in the appendices of this report.
4. Support PWROG Efforts on Generic Licensing	Provided results of OLM data analysis and research, to the PWROG to help establish the path for the generic licensing effort. Participated in meetings and teleconferences and provided technical advice regarding OLM implementation and benefits.

1.5 Plant Participation

The success of this SBIR project is due in large part to the active participation of NPPs during the course of the Phase I, Phase II, and Phase II+ efforts. The plants each participated in the project by providing plant data, engineering resources, and/or technical services to AMS. For the Phase I project, the operating plant data used for evaluating OLM algorithms was provided by EDF Energy's (formerly British Energy) Sizewell B plant. For the Phase II project, Unit 1 of the Southern Nuclear Operating Company's (SNOC) Farley plant was chosen as the site for the full demonstration of the OLM system. In the Phase II+ project, data from Farley Units 1 and 2 as well as Units 1 and 2 of Dominion's North Anna plant were evaluated.

1.6 Project Personnel

The work for this project was performed under the guidance of the principal investigator, Dr. H.M. Hashemian, who led the group of AMS engineers in the research and development of this project until its completion in June 2011. Dr. Hashemian provided the DOE project manager, Dr. M.A. Feltus, with quarterly status reports throughout the course of the Phase I, Phase II, and Phase II+ projects, and Dr. Feltus in turn provided constructive criticism and guidance as necessary. Table 1.5 lists the primary project participants from AMS and their respective roles during the Phase I, Phase II, and Phase II+ projects.

1.7 Organization of this Report

Section 2 of this report provides descriptions of the OLM data and analysis methods that were used to generate the results for this report.

Section 3 presents summaries of the OLM analysis for each of the four reactors evaluated in this project as well as interesting observations made during the analysis.

Section 4 describes some of the lessons learned over the course of the project including experiences with OLM data acquisition, common OLM analysis pitfalls, and evaluations of the analytical modeling technique used during the project.

Table 1.5 AMS Participants in the SBIR Project

NAME AND CREDENTIALS	ROLE IN THIS PROJECT	PHOTO
H.M. Hashemian Ph,D., Engineering Sciences Ph.D., Nuclear Engineering D.E., Electrical Engineering AMS President and CEO.	Principal Investigator (PI). Responsible for overall technical management of the Phase I, Phase II, and Phase II+ projects and the commercialization effort.	
B.D. Shumaker M.S., Computer Science Senior Software Development Engineer	Served as the project manager for the Phase II and Phase II+ projects. Mr. Shumaker was also responsible for development of OLM static models, software modules, and OLM analysis. He also assisted the PI in the writing of the quarterly progress reports and the Phase I, Phase II, and Phase II+ final reports.	
G.W. Morton M.S., Electrical Engineering Software Development Manager	Assisted in the development of the OLM dynamic modeling software and the development of the OLM system hardware. Mr. Morton was also involved in developing the static OLM software, and writing the Phase I, Phase II, and Phase II+ final reports. He also served as the project manager for the Phase I project.	
R.J. Wunderlich M.S., Electrical Engineering Systems Engineer	Assisted in the development of OLM static models and software, and contributed in the writing of the Phase II report.	
S.D. Caylor M.S., Electrical Engineering Systems Engineer	Assisted in the development of OLM dynamic auto-regressive models and the development of the OLM system hardware. Mr. Caylor also assisted in writing the Phase II and Phase II+ final reports.	
D. W. Mitchell B.S., Mechanical and Aerospace Engineering Technical Services Manager	Worked as the technical and administrative assistant to the PI. He coordinated the manpower allotments for the project team, and the administrative personnel, in addition to being responsible for all financial matters. Mr. Mitchell also served as the plant contact for the commercialization effort.	
C. D. Sexton B.A.S., Electronics Engineering Technology Data Analyst; System Implementation	Assisted in the development and testing of the OLM system hardware.	

Section 5 provides descriptions of the commercialization activities that have been performed during the course of the project as well as a description of the PWROG generic licensing effort currently underway.

This report also provides several Appendices that include background information on the concept of OLM (Appendix A), details of various OLM analysis techniques (Appendices B, C, and D), and a description of the OLM system used to produce the results for this report (Appendix E). Detailed OLM result summaries and plots for Farley Units 1 and 2 and North Anna Units 1 and 2 are provided in Volume II.

2. OLM DATA AND ANALYSIS METHODOLOGY

2.1 Background

The concept of OLM, illustrated in Figure 2.1 and explained in more detail in Appendix A, is centered around utilizing the information available from existing plant sensors to quantify the health status of sensors and systems in nuclear power plants. In general, the data that provides the health information can be classified as *static* or *dynamic*, with each type of data providing different information about the sensor or system from which it originates.

Static data, typically retrieved from the plant computer or data historian at rates of up to 1 Hz, can be used to recognize slow moving changes in sensors or plant processes that are a result of drift, degradation, or gradual equipment failure. OLM applications that take advantage of the information contained in static data include on-line calibration monitoring, RTD cross-calibration, thermocouple cross-calibration, and equipment condition assessment. The static data analysis techniques of redundant sensor averaging and kernel regression are described in Appendices B and C of this report, respectively.

Dynamic data requisition, which typically requires sampling at higher frequencies than available from the plant computer (100 Hz to 1 kHz) requires a dedicated data acquisition system for retrieval. OLM applications that use dynamic data include dynamic response of pressure transmitters, predictive maintenance of reactor internals (including core barrel vibration), detection of core flow anomalies, and life extension of neutron detectors. Dynamic data is analyzed using the noise analysis technique, which is described in detail in Appendix D.

The purpose of the Phase II project was to develop an OLM system that integrates both static and dynamic data retrieval and analysis into one common software/hardware framework and demonstrate its use on data from an operating nuclear power plant. The OLM system developed during Phase II (Figure 2.2) incorporates both static and dynamic data analysis modules and data retrieval capabilities, and was demonstrated in Phase II on data from Unit 1 of the Farley Nuclear Power Plant [2]. A description of the OLM system developed during Phase II and subsequently used for the analysis provided in this report is provided in Appendix E.

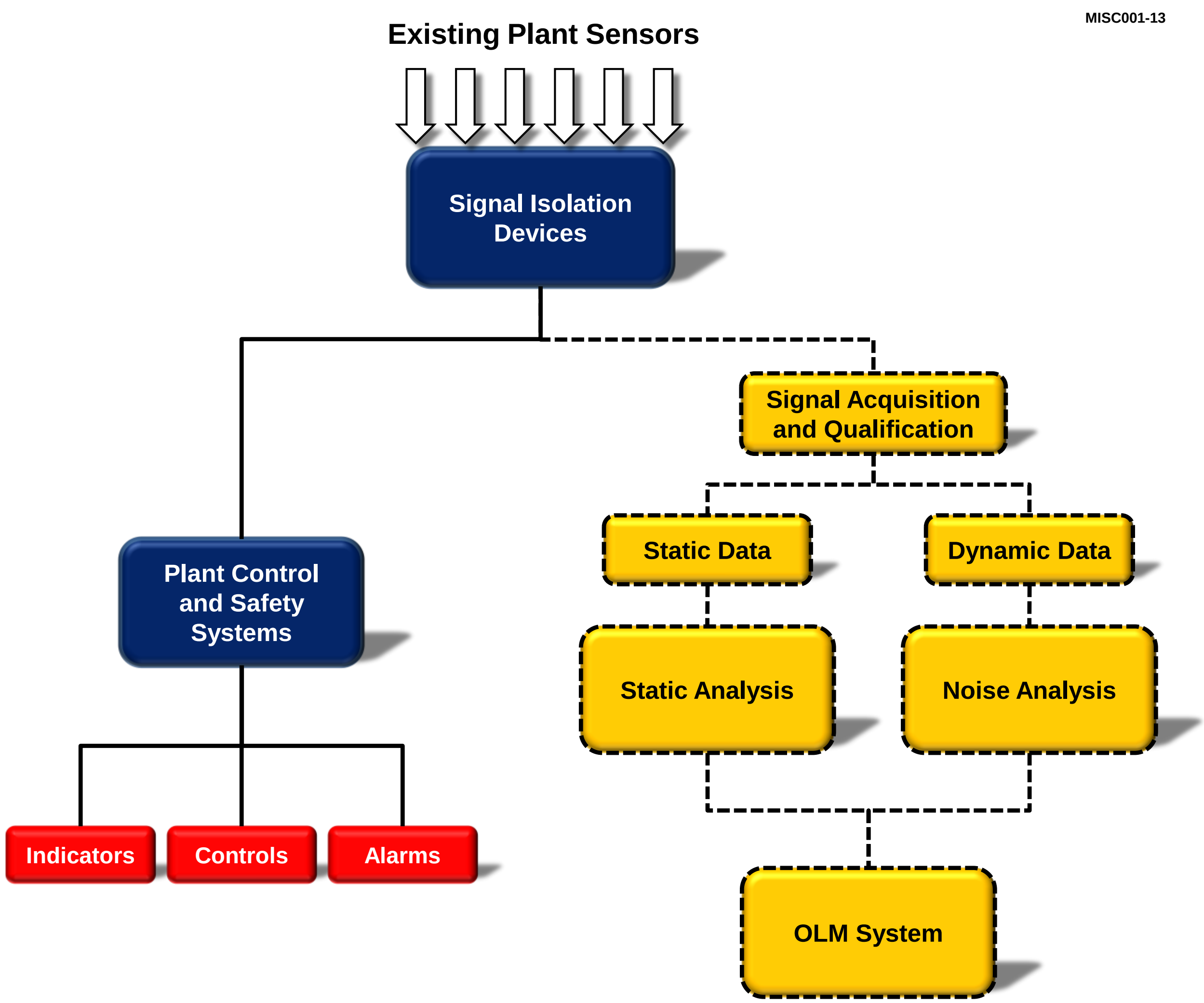


Figure 2.1 OLM Concept

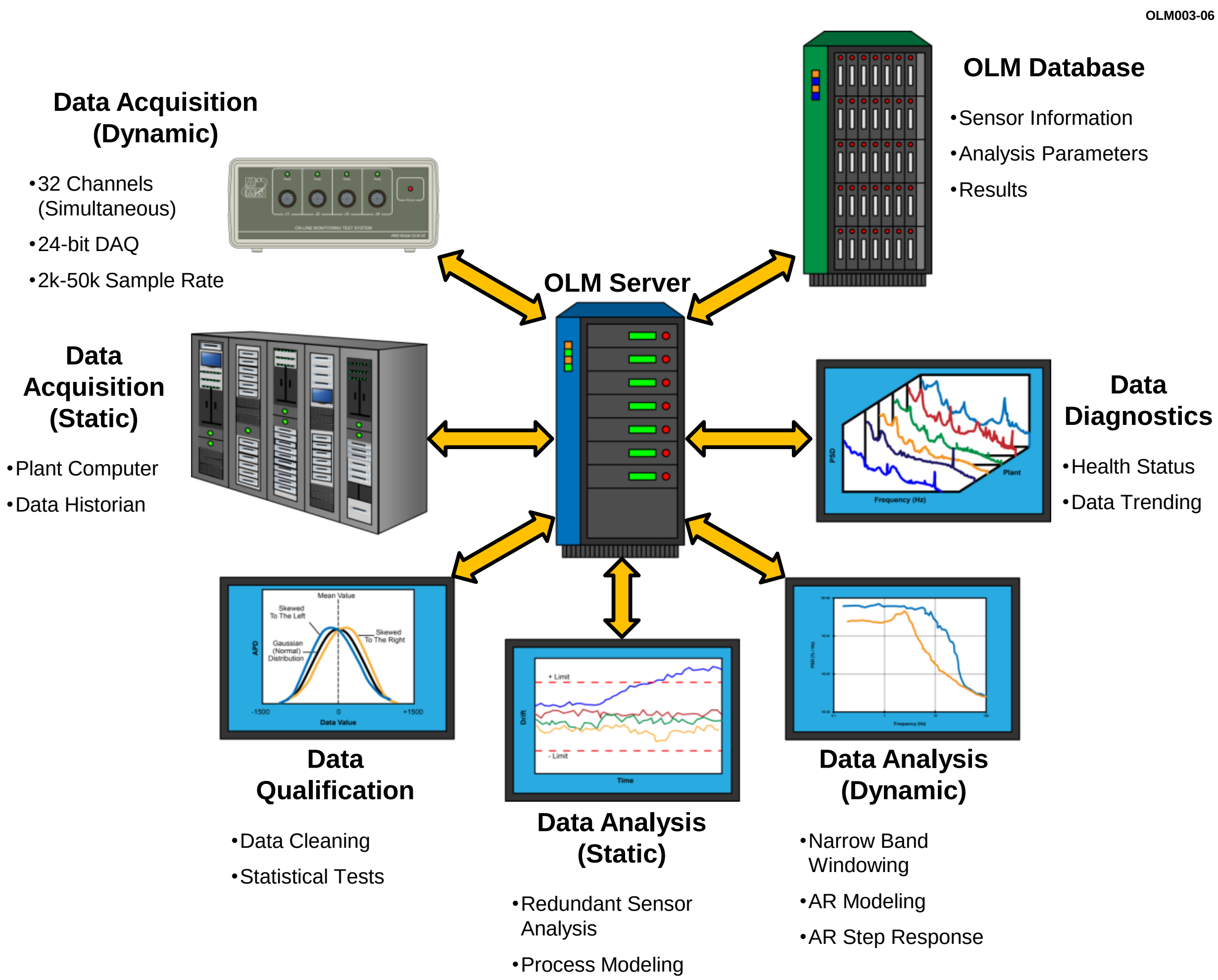


Figure 2.2 OLM System Developed in Phase II

2.2 OLM Data for the Phase II+ Project

As previously discussed, the purpose of the Phase II+ project was to expand the OLM analysis demonstration to include data from a total of four nuclear reactors. Engineers from Southern Nuclear Operating Company (SNOC) and Dominion participated in the project by providing OLM data from the Farley nuclear power plant (Units 1 and 2) and the North Anna nuclear power plant (Units 1 and 2). The SNOC and Dominion personnel were primarily interested in applying on-line calibration monitoring for the purpose of transmitter calibration interval extension, because of the potential cost-benefits that have been realized by its implementation at the Sizewell B plant in the United Kingdom [3]. The OLM analysis for the Phase II+ project, therefore, was focused on the transmitters in each plant that would benefit the most from having their calibration intervals extended. Table 2.1 provides a listing of the services and number of transmitters in each service that were analyzed for the Farley and North Anna plants. Over the course of the project, plant personnel retrieved a 12-hour window of transmitter data each month from the plant computer and sent it to AMS via FTP for analysis. The static data for each plant was sampled at a rate of 1 sample every ten seconds. Overall, static data for 9 operating cycles were included in the analysis. In addition to the static OLM data, AMS acquired dynamic data from Farley Unit 1 and 2 transmitters to evaluate their dynamic response characteristics. Table 2.2 provides a summary of the OLM data from each reactor that was analyzed for this project.

2.3 OLM Data Analysis Methodology

Static OLM analysis was performed on each of the transmitters by evaluating sensor data with both redundant sensor averaging and empirical modeling analysis techniques. With the exception of the Wide Range Steam Generator Level and RCS Pressure transmitters, each reactor analyzed has at least 2 redundant transmitters in each service. Table 2.3 lists the number of redundant sensors for the services at Farley and North Anna that were analyzed.

Empirical modeling analysis was used both to analyze the sensor health for those transmitters that are not redundant as well as providing another diverse method for evaluating the redundant sensors. As described in the Phase II report [2], AMS employed the Auto Associative Kernel Regression (AAKR) methodology to perform empirical modeling analysis. Table 2.4 lists the AAKR models that were created for each reactor as well as the type of diverse sensors used in each model.

Table 2.1 Transmitters Analyzed in Phase II+ Project Per Reactor

Item	Service	Number of Transmitters
1	Steam Flow	6
2	Feedwater Flow	6
3	Steam Generator Level Narrow Range	9
4	Steam Generator Level Wide Range	3
5	Steam Pressure	9
6	Pressurizer Level	3
7	Pressurizer Pressure[1]	3
8	RCS Flow	9
9	RCS Pressure	2
10	Turbine First Stage Pressure	2
11	RWST Level[2]	2
12	Containment Pressure[2]	5

1 Farley Units 1 and 2 include 2 additional Pressurizer Pressure transmitters for a total of 5.

2 Only included in Farley Units 1 and 2

Table 2.2 OLM Data Analyzed for Phase II+

Item	Reactor	Fuel Cycle	Date(s)	OLM Data Type
1	Farley Unit 1	22	April 2008 – April 2009	Static
2	Farley Unit 1	22	March 2009	Dynamic
3	Farley Unit 1	23	April 2009 – October 2010	Static
4	Farley Unit 1	23	June 2009	Dynamic
5	Farley Unit 1	24	November 2010 – July 2011	Static
6	Farley Unit 2	20	August 2009 – April 2010	Static
7	Farley Unit 2	20	March 2010	Dynamic
8	Farley Unit 2	21	May 2010 – July 2011	Static
9	Farley Unit 2	21	July 2010	Dynamic
10	North Anna Unit 1	20	January 2008 – March 2009	Static
11	North Anna Unit 1	21	April 2009 – August 2010	Static
12	North Anna Unit 1	22	November 2010 – April 2011	Static
13	North Anna Unit 2	21	April 2010 – April 2011	Static

Table 2.3 Redundant Services Analyzed for Farley and North Anna

Service	Redundancy
Reactor Coolant System Loop A Flow	3
Reactor Coolant System Loop B Flow	3
Reactor Coolant System Loop C Flow	3
Pressurizer Level	3
Steam Generator A Narrow Range Level	3
Steam Generator B Narrow Range Level	3
Steam Generator C Narrow Range Level	3
Pressurizer Pressure	3
Steam Generator A Outlet Pressure	3
Steam Generator B Outlet Pressure	3
Steam Generator C Outlet Pressure	3
Containment Pressure	3
Steam Generator A Steam Flow	2
Steam Generator B Steam Flow	2
Steam Generator C Steam Flow	2
Feedwater Flow To Steam Generator A	2
Feedwater Flow To Steam Generator B	2
Feedwater Flow To Steam Generator C	2
Refueling Water Storage Tank Level	2
Turbine First Stage Pressure	2

Table 2.4 AAKR Models Developed for Farley and North Anna

AAKR Model	# of Sensors	Sensor Types
Steam Generator (A,B,and C)	20	1. Steam Flow (2) 2. Feedwater Flow (2) 3. SG NR Level (3) 4. SG WR Level (1) 5. SG Outlet Pressure (3) 6. TBIN FS Pressure (2) 7. NI Power Range (4) 8. RCS Hot Leg Temp.WR (1) 9. Feedwater Inlet Temp. (2)
Pressurizer	15	1. PZR Level (3) 2. PZR Pressure (3) 3. NI Power Range (4) 4. RCS Hot Leg Temp.WR (3) 5. PZR Water Temp. (1) 6. PZR Steam Temp. (1)
RCS Loop (A,B, and C)	7	1. RCS Flow (3) 2. RCS WR Pressure (1) 3. RCS Cold Leg Temp. WR (1) 4. RCS Cold Leg Temp. NR (1) 5. RCS Hot Leg Temp. WR (1)

2.4 OLM Data Analysis Methodology

A number of plots and tables are produced by the OLM system software to aid in analysis and present the results. Descriptions of these plots and tables as well as examples of each are provided below:

1. **Steady State Deviation Plot**. This plot (Figure 2.3) presents the average deviation of each sensor from the average of its redundant peers (excluding any outliers) for each time period (typically one month) that is provided during the steady state operation. Deviations that exceed the OLM acceptance criteria (shown in Figure 2.3 as red dashed lines), are indicative of a potential problem with the sensor.

   In the analysis performed for Phase II+, the OLM acceptance criteria for deviation, drift, and empirical modeling analysis were set to 0.75% of the sensors' calibrated ranges after discussions with plant personnel from Farley and North Anna.

2. **Steady State Drift Analysis**. This plot (Figure 2.4) provides a visualization of how the deviation for a given sensor changes over time. Drift is calculated from the steady state deviation analysis by subtracting the first month's deviation from each signal (i.e. zeroing the first month). The OLM acceptance criteria limits for drift are shown with red dashed lines.

3. **Steady State Residual Analysis (Empirical Modeling)**. This plot (Figure 2.5) presents the average difference between the model estimate and the measured data (also known as the residual) by subtracting the model process estimate from each signal for each month of steady state data. This will identify drift from the training data that is due to sensor drift, process drift, or a common mode drift. Similar to the deviation and drift plots the OLM acceptance criteria limits are shown with red dashed lines.

4. **Transient Deviation Analysis (if available)**. This plot (Figure 2.6) presents the deviation of each transmitter from the average of its peers plotted as a function of the transmitter's operating range as the process experiences a transient such as startup or shutdown. Some services do not transition through much of their range during a cycle, and in this case a transient deviation plot is not produced. On the other hand, some services experienced multiple transients during the observation period, resulting in multiple transient deviation plots for some services. Transient deviation analysis plots also incorporate OLM acceptance criteria limits that are denoted by red dashed lines.

5. **Data Quality Statistics**. Data quality statistics are presented by four plots and a table (Figure 2.7). The four plots consist of the mean, standard deviation, skewness, and kurtosis calculated for each month of steady state data. The table contains the average value of each statistic for each sensor in the four plots.

6. **Static Summary Table**. This table (Table 2.5) list the sensor tag name, service, the result of the steady state data analysis each month, the drift result, the final pass or fail result, and a comment for each sensor. An 'R' indicates the Redundant sensor analysis acceptance limits were exceeded. An 'M' indicates the empirical model analysis acceptance limits were exceeded. A 'D' indicates the drift limits were exceeded.

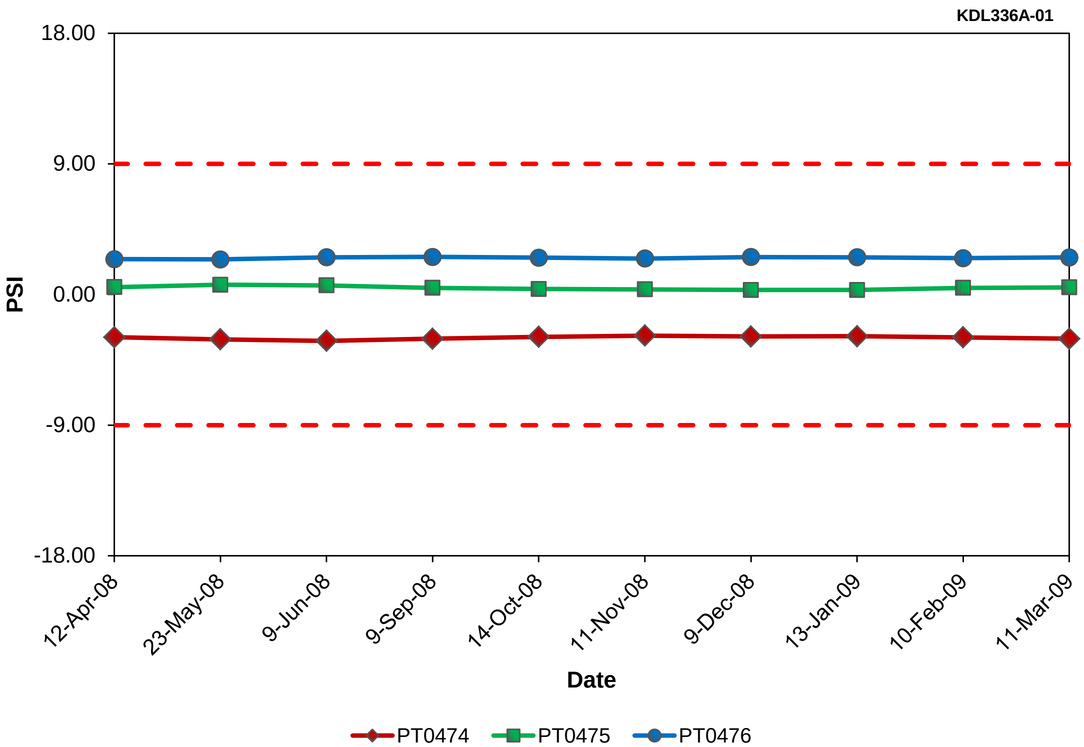


Figure 2.3 Steady-State Deviation Example

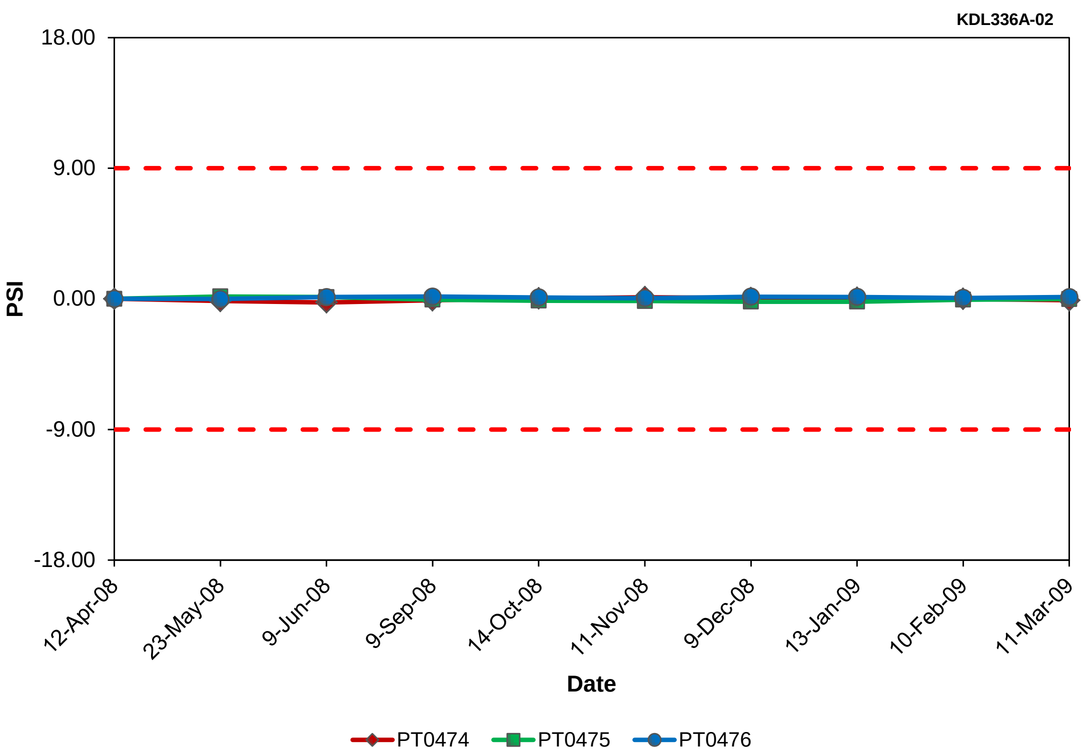


Figure 2.4 Steady-State Drift Example

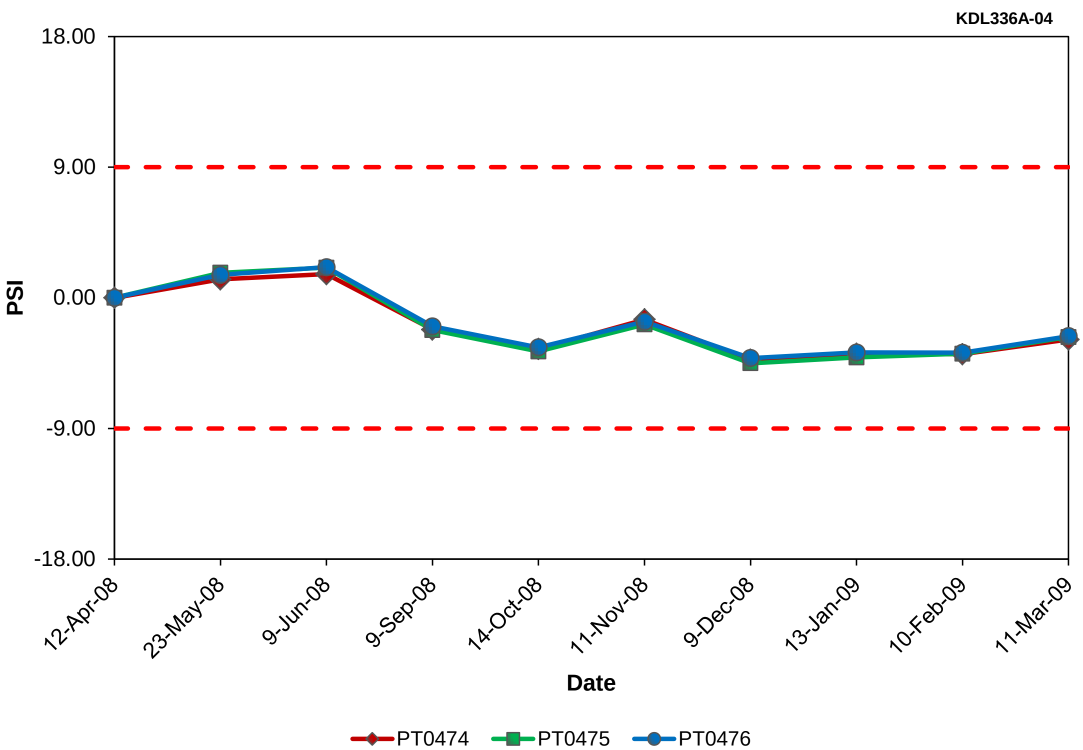


Figure 2.5 Steady-State Residual Example

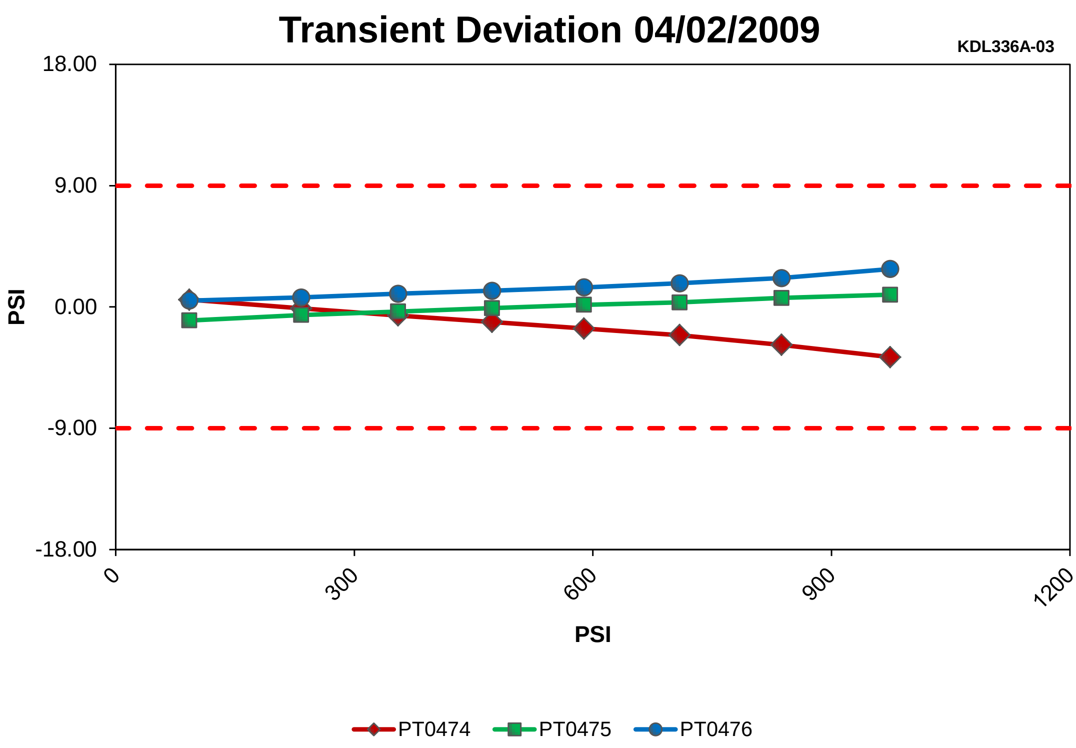
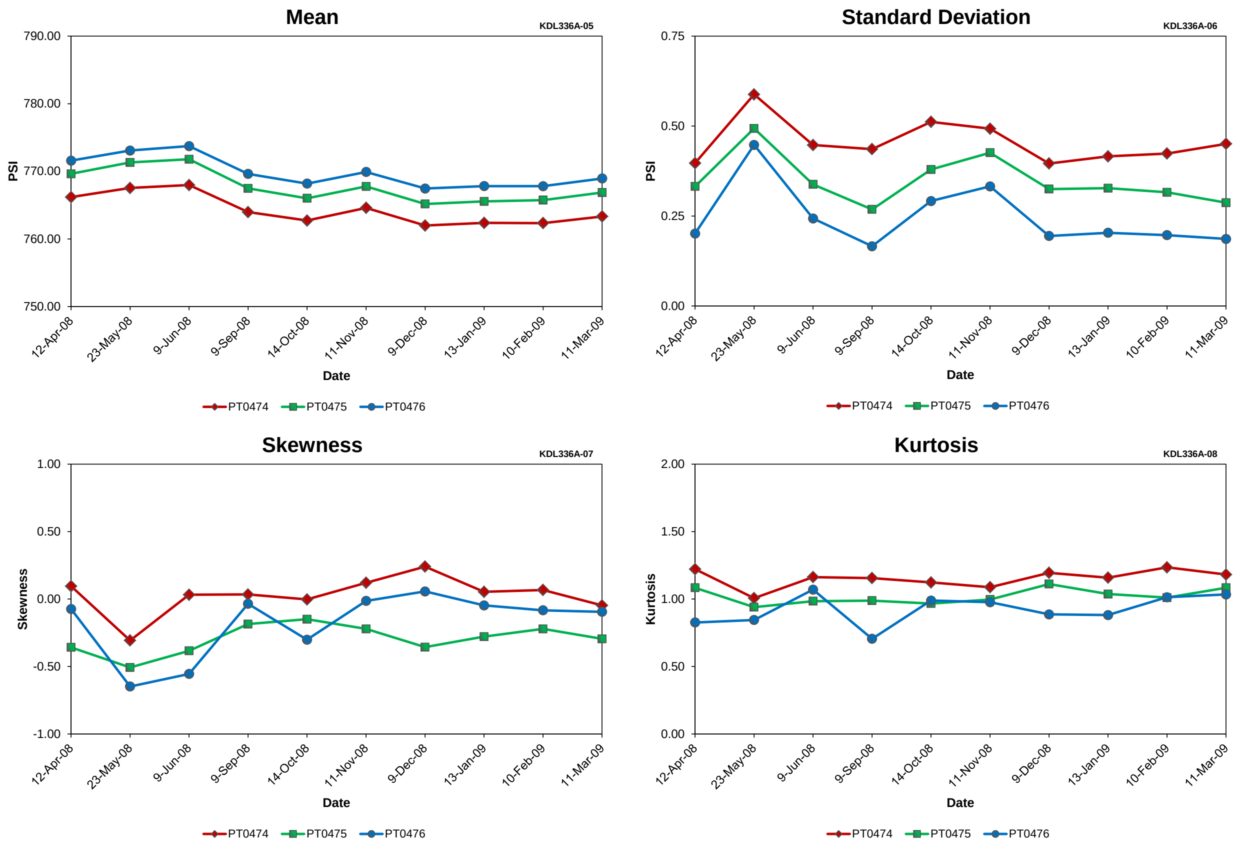


Figure 2.6 Transient Deviation Example



Data Quality Statistics Plots

Data Quality Summary Table Example

Result Type	Tag Names		
	PT0474	PT0475	PT0476
Mean	764.31	767.73	769.82
Std. Dev.	0.46	0.35	0.25
Skewness	0.03	-0.30	-0.18
Kurtosis	1.15	1.02	0.92

Figure 2.7 Data Quality Statistics Plots and Table

Table 2.5 Summary Table Sample Results

Item	Tagname	Service	11 Nov 2008	9 Dec 2008	13 Jan 2009	10 Feb 2009	11 Mar 2009	2 Apr 2009	Drift	Final	Comment
1	FE0474B	SG A STEAM FLOW						R		PASS	
2	FE0475B	SG A STEAM FLOW						R		PASS	
3	FE0476B	FW FLOW TO SG A								PASS	
4	FE0477B	FW FLOW TO SG A								PASS	
5	LT0474	SG A NR LEVEL						R		FAIL	
6	LT0475	SG A NR LEVEL	R	R	R	R	R	R		FAIL	Low bias
7	LT0476	SG A NR LEVEL						R		FAIL	
8	LT0477	SG A WR LEVEL	M	M	M	M	M			FAIL	Drift out (AAKR)
9	PT0474	SG A PRESSURE								PASS	
10	PT0475	SG PRESSURE								PASS	
11	PT0476	SG A PRESSURE								PASS	
12	FE0484B	SG B STEAM FLOW								PASS	
13	FE0485B	SG B STEAM FLOW								PASS	
14	FE0486B	FW FLOW TO SG B								PASS	
15	FE0487B	FW FLOW TO SG B								PASS	

R = Exceeded Redundant Sensor Analysis Limits   M = Exceeded Model Analysis Limits   D = Exceeded Drift Limits

7. **Dynamic Parameter Table.** This table (Table 2.6) presents the tag name, service, narrow band PSD window low and high frequency that was trimmed from the wide band PSD, the Auto-Regressive (AR) modeling method, and AR order. Once selected, these parameters are stored in the OLM database and become the basis for future analysis.

   The reader is referred to the Phase II report [2] for more information on AR modeling and parameter selection.

8. **Dynamic Narrow Band PSD Window Selection.** This plot (Figure 2.8) presents a wide band PSD and shows the low and high frequency selection that are used to create the narrow band PSD. The selected parameters are displayed in the table above the plot. This plot is only included if this is the first analysis for this sensor because it will be the same for subsequent analysis.

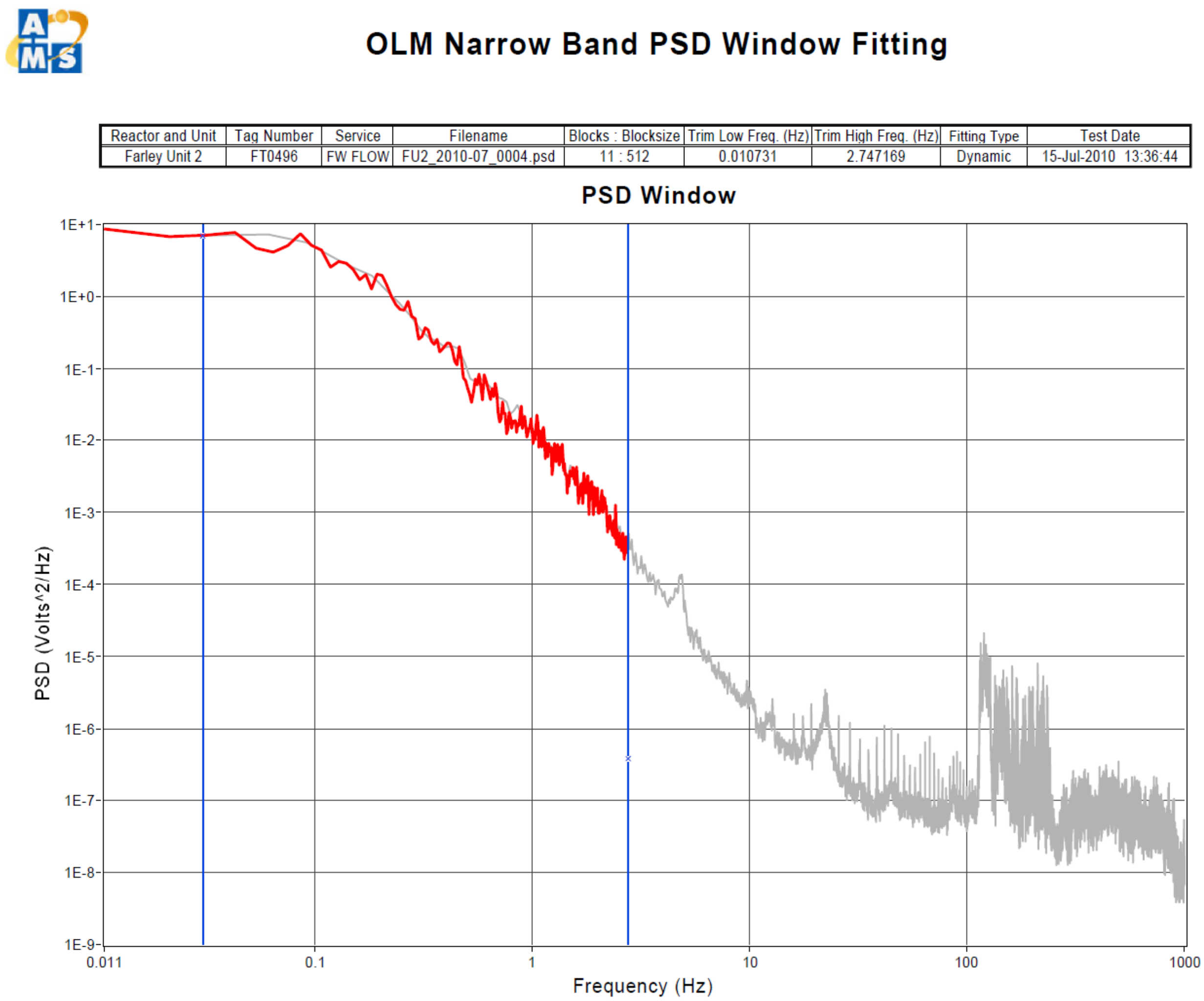
9. **Dynamic Autoregressive Fit of Narrow Band PSD.** This plot (Figure 2.9) displays the narrow band PSD and the AR PSD. The difference between the PSDs is displayed in an Error plot at the bottom with the RMS error displayed. Above the plot is a table with the AR parameters.

10. **Dynamic Comparison of Narrow Band PSDs.** This plot (Figure 2.10) presents the current narrow band PSD and the previous narrow band PSD for comparison. The difference between the PSDs is displayed in an Error plot at the bottom with the RMS error displayed. Above the table are the current PSD parameters. This is only included if there is a previous analysis for comparison.

The appendices in Volume 2 of this report contain the OLM results for Farley Units 1 and 2 and North Anna Units 1 and 2 presented in these previously described plots and tables.

Table 2.6 Dynamic Parameter Table Example

Item	Tag Name	Service	Filename	WB PSD Range (Hz)	Decimator	Trim Block Size	Trim Low Freq.	Trim High Freq.	AR Method	AR Order
1	FT0476	FW FLOW	FU2_2010-07_0004	0.0305 : 1000	364	512	0.0107	2.7472	Forward-Backward	11
2	FT0477	FW FLOW	FU2_2010-07_0003	0.0305 : 1000	364	512	0.0107	2.7472	Least-Squares	17
3	FT0486	FW FLOW	FU2_2010-07_0004	0.0305 : 1000	364	512	0.0107	2.7472	Forward-Backward	11
4	FT0487	FW FLOW	FU2_2010-07_0003	0.0305 : 1000	364	512	0.0107	2.7472	Least-Squares	21
5	FT0496	FW FLOW	FU2_2010-07_0004	0.0305 : 1000	364	512	0.0107	2.7474	Forward-Backward	11
6	FT0497	FW FLOW	FU2_2010-07_0003	0.0305 : 1000	364	512	0.0107	2.7472	Least-Squares	21
7	LT0474	SG LEVEL	FU2_2010-07_0001	0.0305 : 1000	85	256	0.0919	11.7643	Forward-Backward	11
8	LT0475	SG LEVEL	FU2_2010-07_0002	0.0305 : 1000	81	256	0.0964	12.3453	Least-Squares	18
9	LT0476	SG LEVEL	FU2_2010-07_0003	0.0305 : 1000	81	256	0.0964	12.3453	Least-Squares	11
10	LT0484	SG LEVEL	FU2_2010-07_0001	0.0305 : 1000	80	128	0.1953	12.4996	Forward-Backward	11
11	LT0485	SG LEVEL	FU2_2010-07_0002	0.0305 : 1000	80	256	0.0977	12.4996	Least-Squares	18
12	LT0486	SG LEVEL	FU2_2010-07_0003	0.0305 : 1000	85	128	0.1838	11.7643	Least-Squares	20
13	LT0494	SG LEVEL	FU2_2010-07_0001	0.0305 : 1000	83	256	0.0941	12.0478	Forward-Backward	11
14	LT0495	SG LEVEL	FU2_2010-07_0002	0.0305 : 1000	78	256	0.1002	12.8201	Least-Squares	18
15	LT0496	SG LEVEL	FU2_2010-07_0003	0.0305 : 1000	83	256	0.0941	12.0478	Least-Squares	20
16	FT0474	STM FLOW	FU2_2010-07_0003	0.0305 : 1000	29	128	0.5388	34.4817	Least-Squares	20
17	FT0475	STM FLOW	FU2_2010-07_0004	0.0305 : 1000	29	128	0.5388	34.4817	Forward-Backward	11
18	FT0484	STM FLOW	FU2_2010-07_0003	0.0305 : 1000	29	128	0.5388	34.4817	Least-Squares	18
19	FT0485	STM FLOW	FU2_2010-07_0004	0.0305 : 1000	29	128	0.5388	34.4817	Forward-Backward	11
20	FT0494	STM FLOW	FU2_2010-07_0003	0.0305 : 1000	29	128	0.5388	34.4817	Least-Squares	19
21	FT0495	STM FLOW	FU2_2010-07_0004	0.0305 : 1000	29	128	0.5388	34.4817	Forward-Backward	11



Reactor and Unit	Tag Number	Service	Filename	Blocks : Blocksize	Trim Low Freq. (Hz)	Trim High Freq. (Hz)	Fitting Type	Test Date
Farley Unit 2	FT0496	FW FLOW	FU2_2010-07_0004.psd	11 : 512	0.010731	2.747169	Dynamic	15-Jul-2010 13:36:44

Figure 2.8 Dynamic Narrow Band PSD Window Selection Example

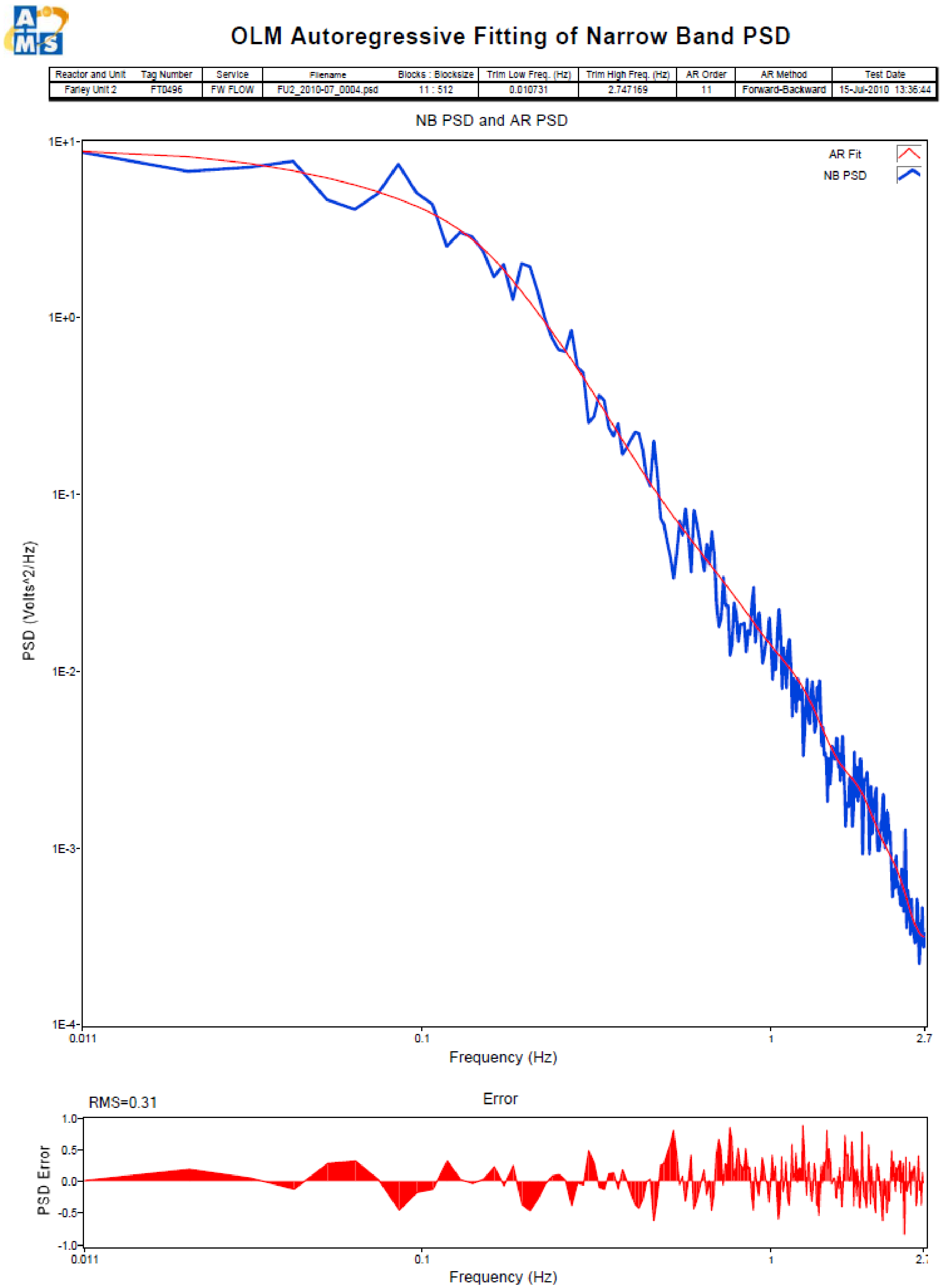


Figure 2.9 Dynamic Autoregressive Fit of Narrow Band PSD Example

OLM DYNAMIC ANALYSIS RESULTS COMPARE

Reactor and Unit	Tag Number	Service	Filename	Blocks : Blocksize	Trim Low Freq. (Hz)	Trim High Freq. (Hz)	AR Order	AR Method	Test Date
Farley Unit 2	FT0496	FW FLOW	FU2_2010-07_0004.psd	11 : 512	0.010731	2.747169	11	Forward-Backward	15-Jul-2010 13:36:44

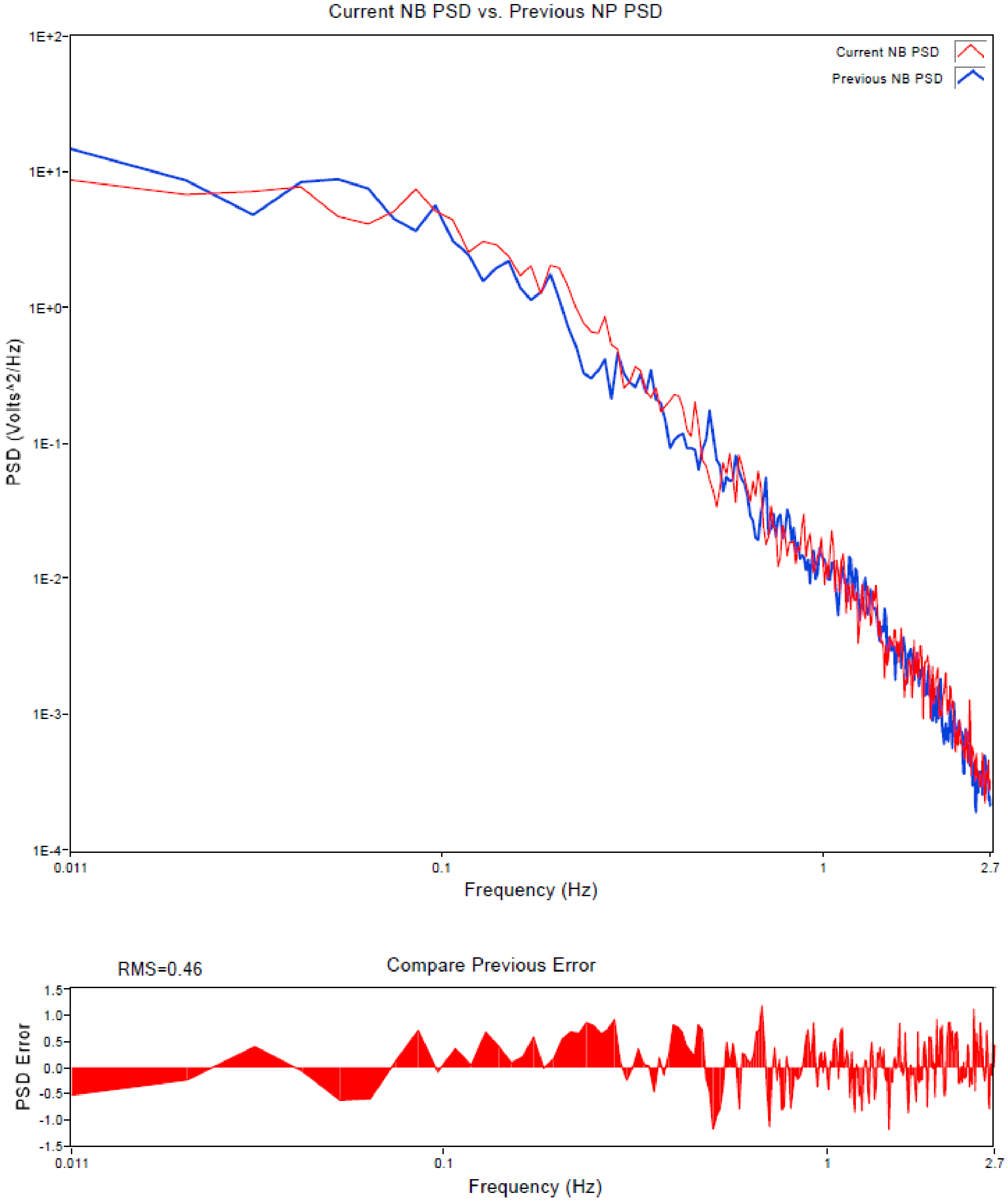


Figure 2.10 Dynamic Comparison of Narrow Band PSDs Example

3. OLM ANALYSIS SUMMARIES

This section summarizes the results of the OLM analysis performed on Farley Units 1 and 2 and North Anna Units 1 and 2 during the project. Also included in this section are examples of transmitters that exhibited problems during the observed period. It should be noted that the majority of transmitters evaluated during this project did not exhibit drift or show problems of any kind during their fuel cycles. This is to be expected as one of the core reasons for employing OLM for transmitter calibration extension is to demonstrate that typical nuclear power plant transmitters do not drift from cycle to cycle. The appendices in Volume 2 of this report provide a full set of OLM analysis plots and tables for all the transmitters analyzed for this project.

3.1 Farley Unit 1 Cycle 22

The OLM analysis for Farley Unit 1 Cycle 22 covers a period between April 2008 and April 2009 and includes 10 months of steady-state data, transient data from plant shutdown, and dynamic data just before shutdown in March 2009. Of the 59 transmitters that were analyzed during this cycle, 7 were identified with potential problems. These transmitters are listed in Table 3.1.

SG A NARROW RANGE LEVEL and SG A WIDE RANGE LEVEL transmitters with potential problems are shown in Figures 3.1 and 3.2, respectively. As shown on the steady-state deviation results in Figure 3.1, narrow range level transmitter LT0475 exhibits a low bias throughout the cycle which causes it to exceed the lower OLM acceptance criteria. Wide range level transmitter LT0477, on the other hand exhibits a gradual drift over Cycle 22 detected from the modeling analysis results, which results in it exceeding its lower OLM acceptance criteria from October 2008 to March 2008 (Figure 3.2).

SG B OUTLET PRESSURE transmitter PT0484 also exhibits a low bias throughout the cycle which causes it to exceed its OLM acceptance limits (Figure 3.3).

PRESSURIZER LEVEL transmitter LT460 drifts above the upper OLM acceptance criteria limits during the cycle as shown in Figure 3.4.

Dynamic OLM data taken on the steam flow, narrow range SG levels and feedwater flow transmitters during this cycle did not reveal any problems with the dynamic characteristics of the transmitters.

Table 3.1 Farley Unit 1 Transmitters with Potential Problems (Cycle 22)

Item	Tagname	Service	Comment
1	LT0474	SG A NARROW RANGE LEVEL	Out in low and high calibrated range.
2	LT0475	SG A NARROW RANGE LEVEL	Low bias.
3	LT0476	SG A NARROW RANGE LEVEL	Out in low and high calibrated range.
4	LT0477	SG A WIDE RANGE LEVEL	Drift over cycle.
5	PT0484	SG B OUTLET PRESSURE	Low bias.
6	LT0460	PRESSURIZER LEVEL	High bias and drift.
7	PT0952	CONTAINMENT PRESSURE	High bias and span shift.

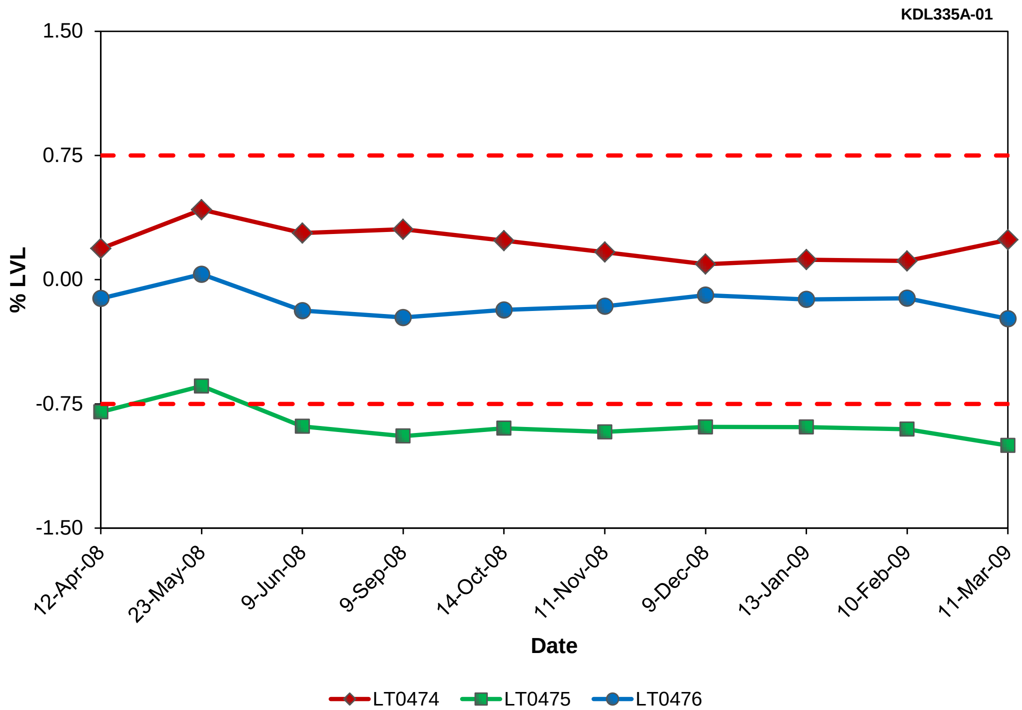


Figure 3.1 Steady-State Deviation SG A Level (Cycle 22)

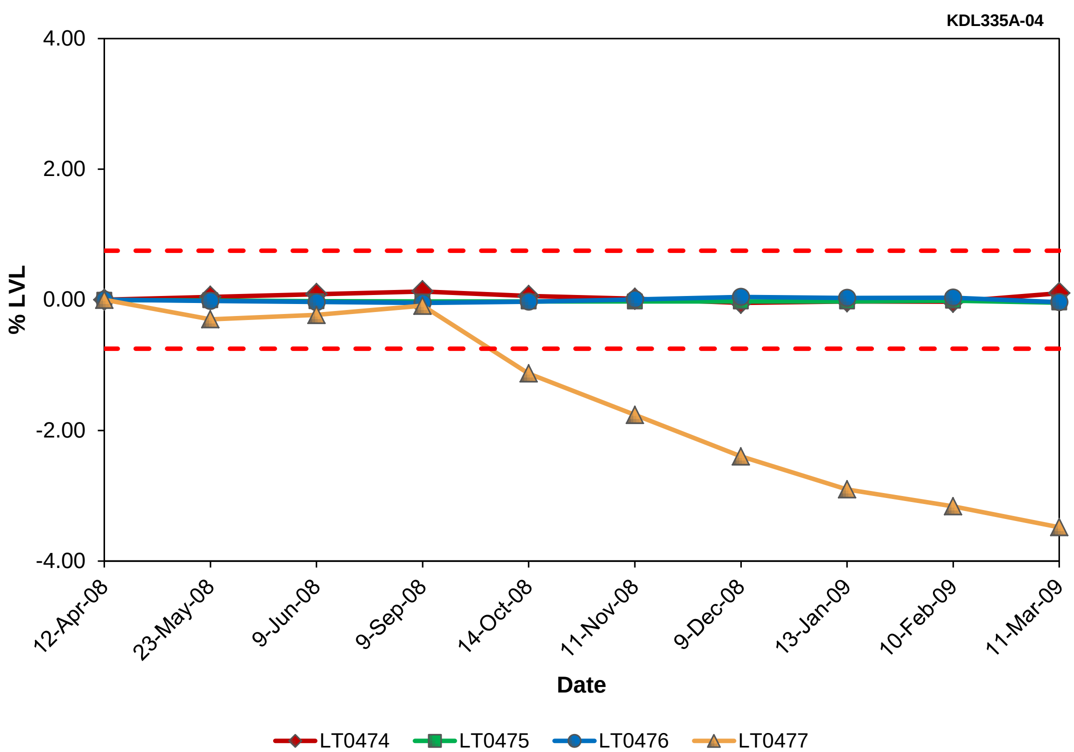


Figure 3.2 Model Analysis SG A Level (Cycle 22)

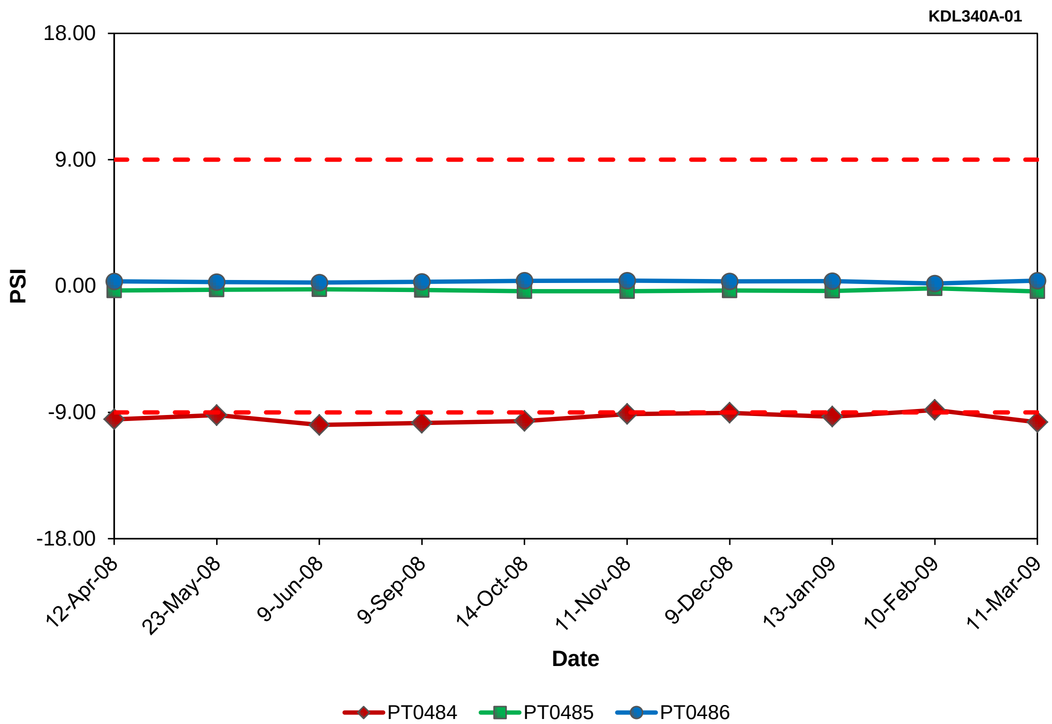


Figure 3.3 Steady-State Deviation SG B Outlet Pressure (Cycle 22)

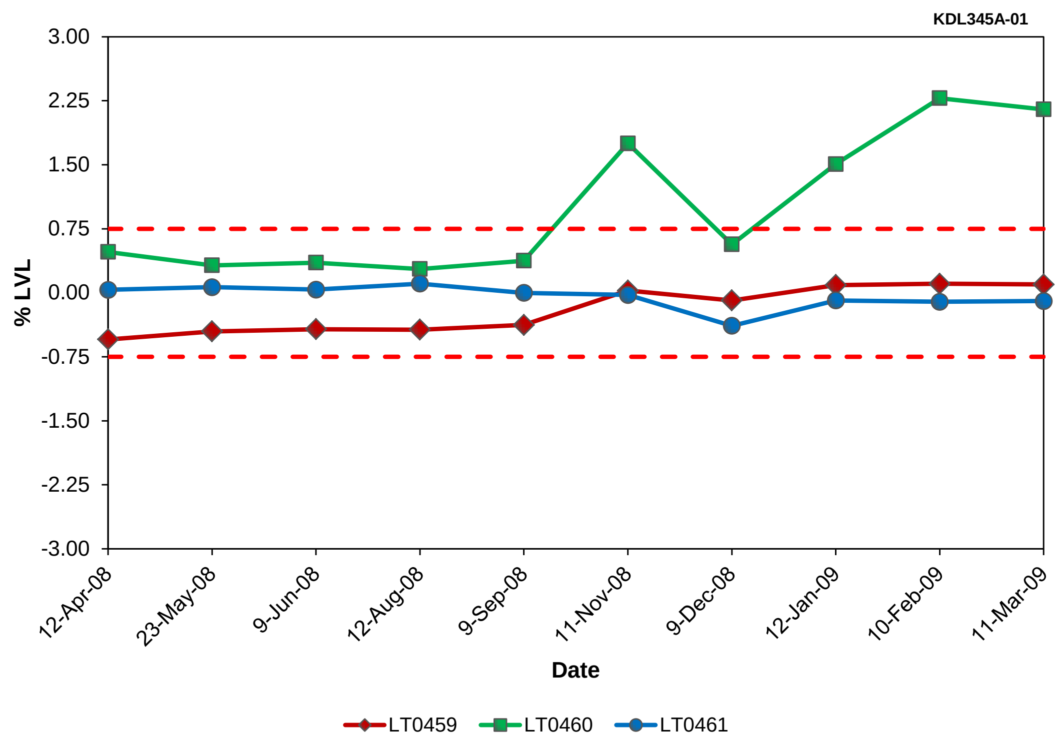


Figure 3.4 Steady-State Drift Pressurizer Level (Cycle 22)

3.2 Farley Unit 1 Cycle 23

The OLM analysis for Farley Unit 1 Cycle 23 covers a period between startup in April/May 2009, 17 months of steady-state data, transient data from plant shutdown in October 2010, and dynamic data taken shortly after startup in June 2009. Of the 59 transmitters that were analyzed during this cycle, 6 were identified with potential problems. These transmitters are listed in Table 3.2.

SG A LEVEL NARROW RANGE transmitters exhibit a bias between them throughout the cycle, which causes LT0475 and LT0474 to exceed the OLM acceptance criteria for deviation (Figure 3.5).

SG A WIDE RANGE LEVEL transmitter LT0477 is shown to drift low during the cycle by the model analysis (Figure 3.6).

PRESSURIZER PRESSURE transmitter PT0455 exhibits a low bias throughout the cycle as shown in Figure 3.7.

RCS LOOP C FLOW transmitter FE0434 exhibits a low bias throughout the cycle which causes it to exceed its lower OLM acceptance criteria limit (Figure 3.8).

Dynamic OLM data taken on the steam flow, narrow range SG levels and feedwater flow transmitters during this cycle did not reveal any problems with the dynamic characteristics of the transmitters.

3.3 Farley Unit 1 Cycle 24

The OLM analysis for Farley Unit 1 Cycle 24 covers a period between startup in November 2010 and 9 months of steady-state data through July 2011. Of the 61 transmitters that were analyzed during this cycle (2 Containment Pressure transmitters were added in Cycle 24), 4 were identified with potential problems. These transmitters are listed in Table 3.3.

SG A WIDE RANGE LEVEL transmitter LT0477 exhibits a low bias which causes it to exceed its lower OLM acceptance limits throughout the cycle (Figure 3.9).

PRESSURIZER LEVEL transmitter LT0459 drifts low relative to the 2 other pressurizer level transmitters during the cycle and exceeds it lower OLM acceptance criteria (Figure 3.10). PRESSURIZER PRESSURE transmitter PT0459 exhibits a high bias throughout the cycle (Figure 3.11).

RCS LOOP A FLOW transmitter FE0416 exhibits a low bias throughout the cycle (Figure 3.12).

Table 3.2 Farley Unit 1 Transmitters with Potential Problems (Cycle 23)

Item	Tagname	Service	Comment
1	LT0474	SG A NARROW RANGE LEVEL	Significant dev. between transmitters
2	LT0475	SG A NARROW RANGE LEVEL	Significant dev. between transmitters
3	LT0476	SG A NARROW RANGE LEVEL	Significant dev. between transmitters
4	LT0477	SG A WIDE RANGE LEVEL	Drift over cycle.
5	PT0455	PRESSURIZER PRESSURE	Low bias.
6	FE0434	RCS LOOP C FLOW	Low bias.

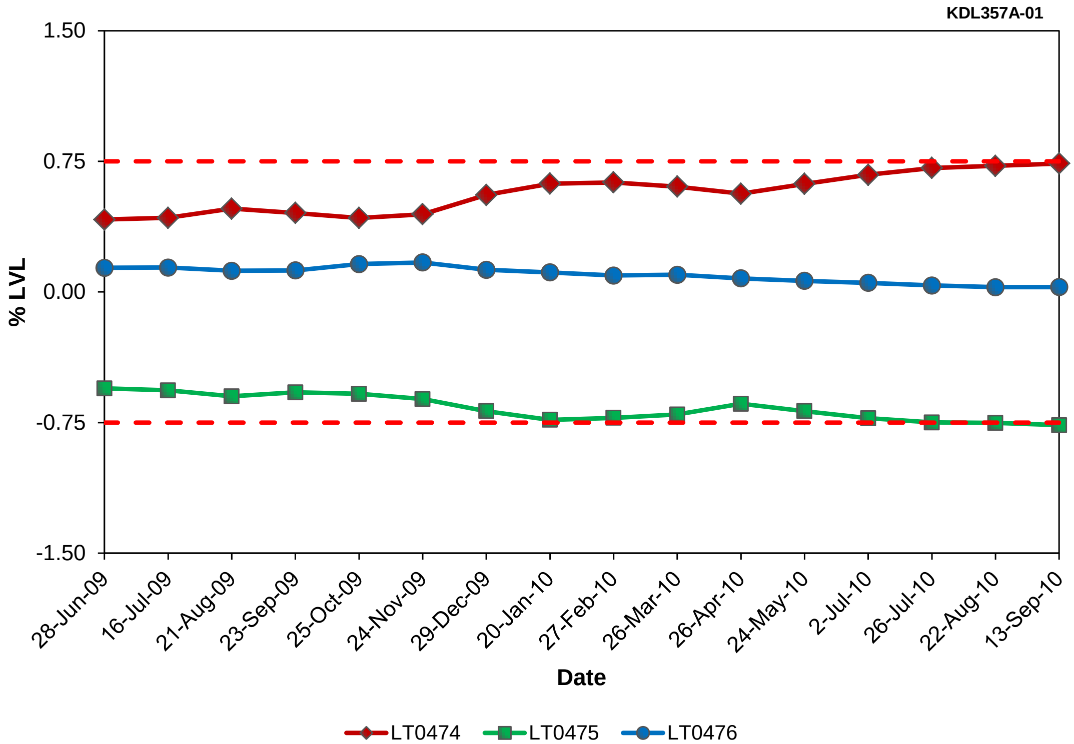


Figure 3.5 SG A LEVEL Steady-State Deviation at Farley Unit 1 (Cycle 23)

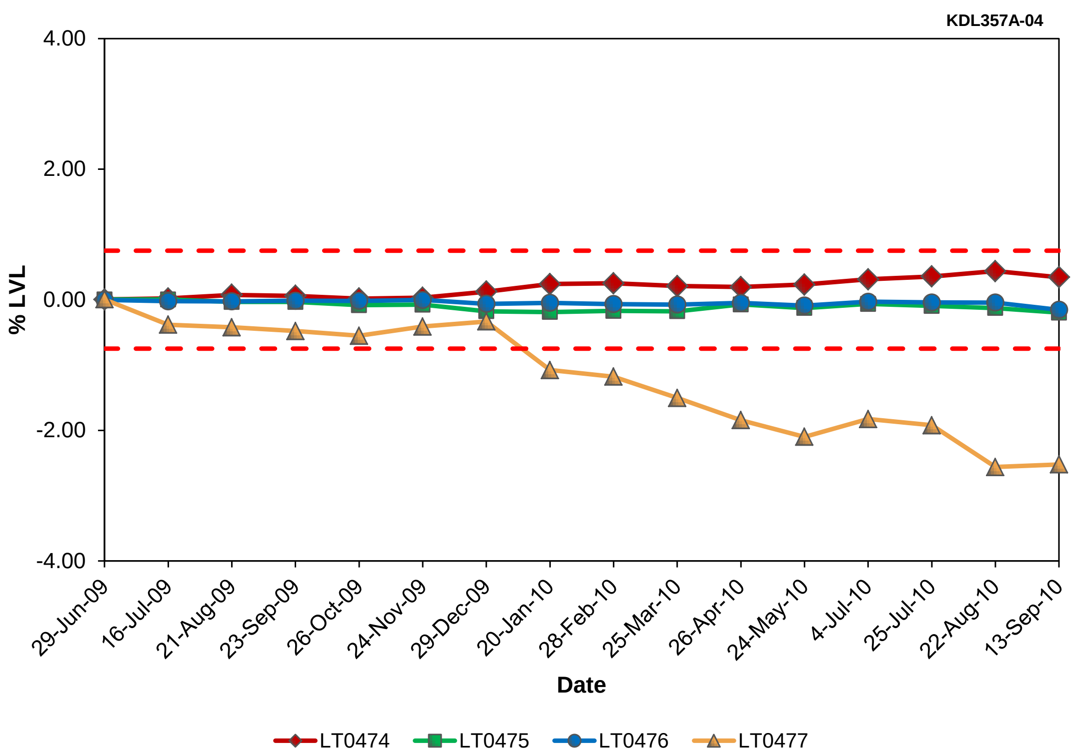


Figure 3.6 SG A LEVEL Model Analysis at Farley Unit 1 (Cycle 23)

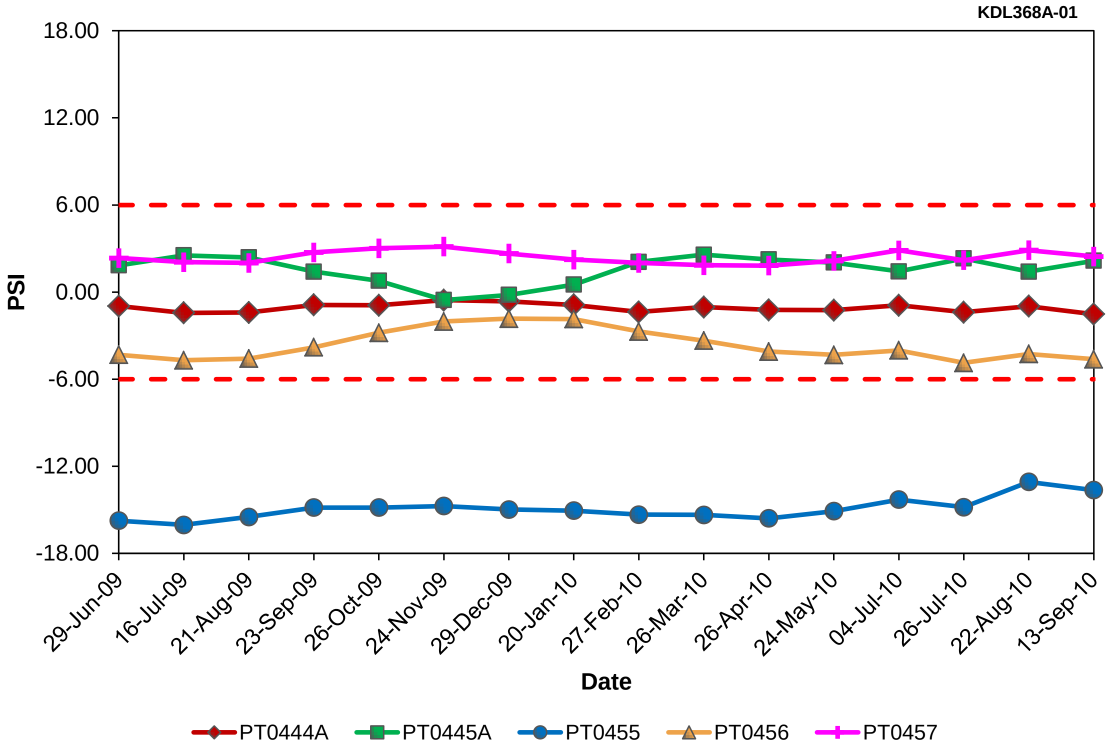


Figure 3.7 PRESSURIZER PRESSURE Steady-State Deviation at Farley Unit 1 (Cycle 23)

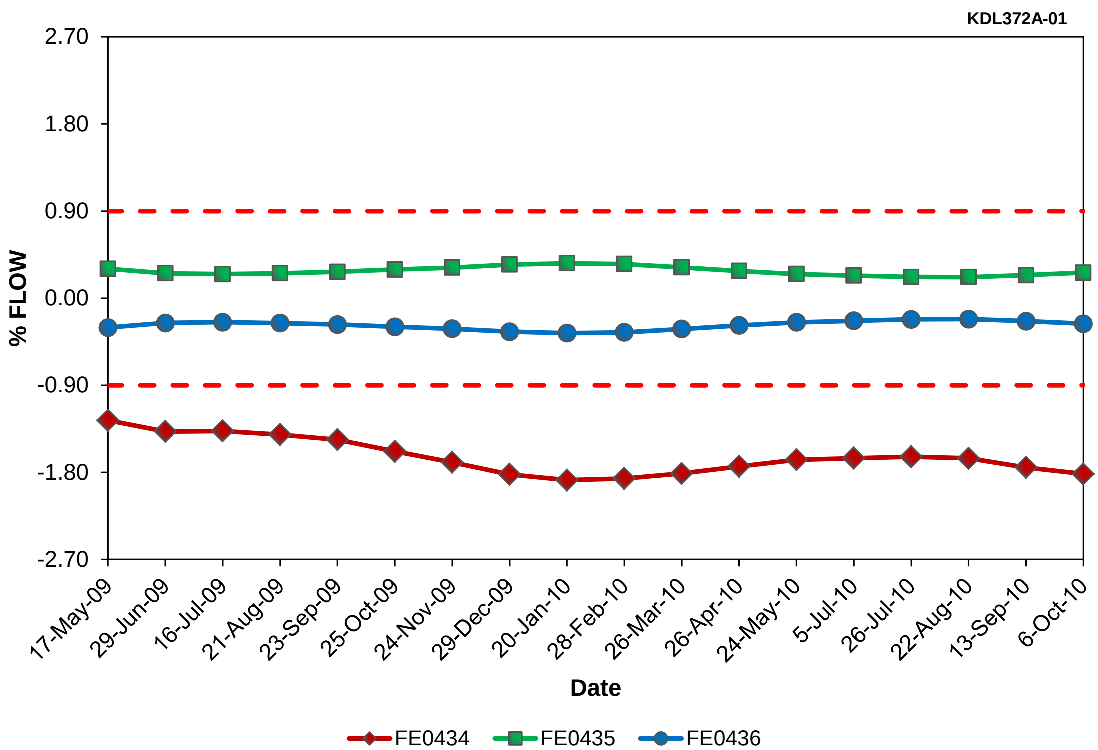


Figure 3.8 RCS LOOP C FLOW Steady-State Deviation at Farley Unit 1 (Cycle 23)

Table 3.3 Farley Unit 1 Transmitters with Potential Problems (Cycle 24)

Item	Tagname	Service	Comment
1	LT0477	SG A WIDE RANGE LEVEL	Low bias.
2	LT0459	PRESSURIZER LEVEL	Low drift.
3	PT0456	PRESSURIZER PRESSURE	High bias.
4	FE0416	RCS LOOP A FLOW	Low bias.

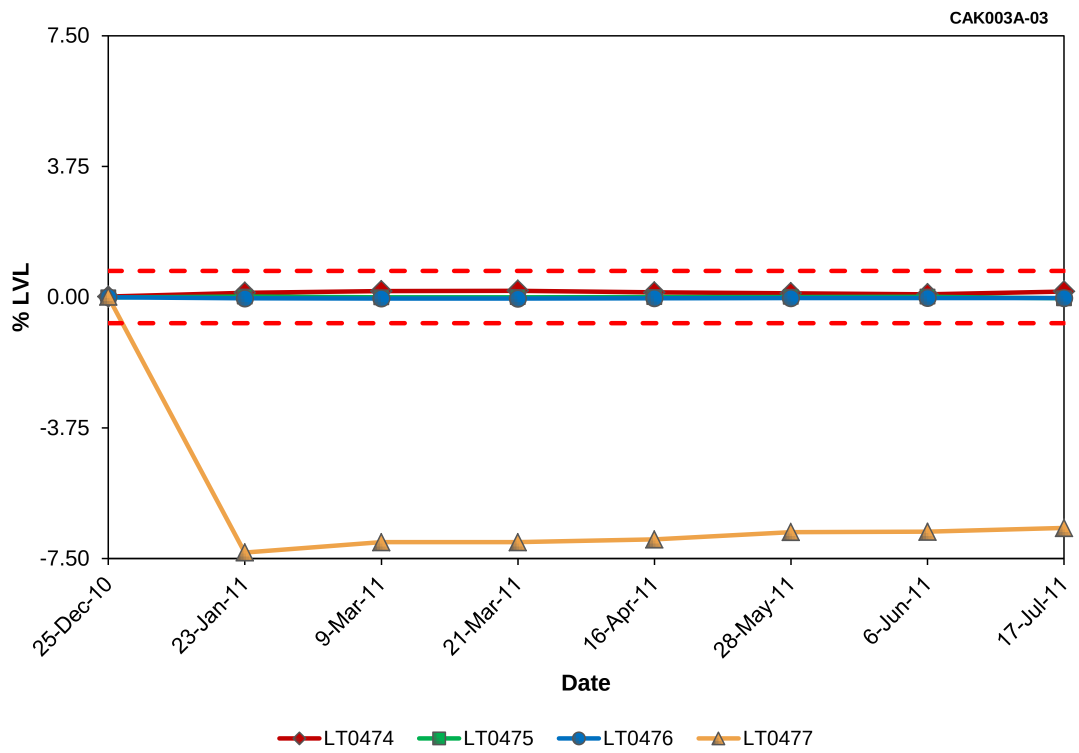


Figure 3.9 SG A LEVEL Model Analysis at Farley Unit 1 (Cycle 24)

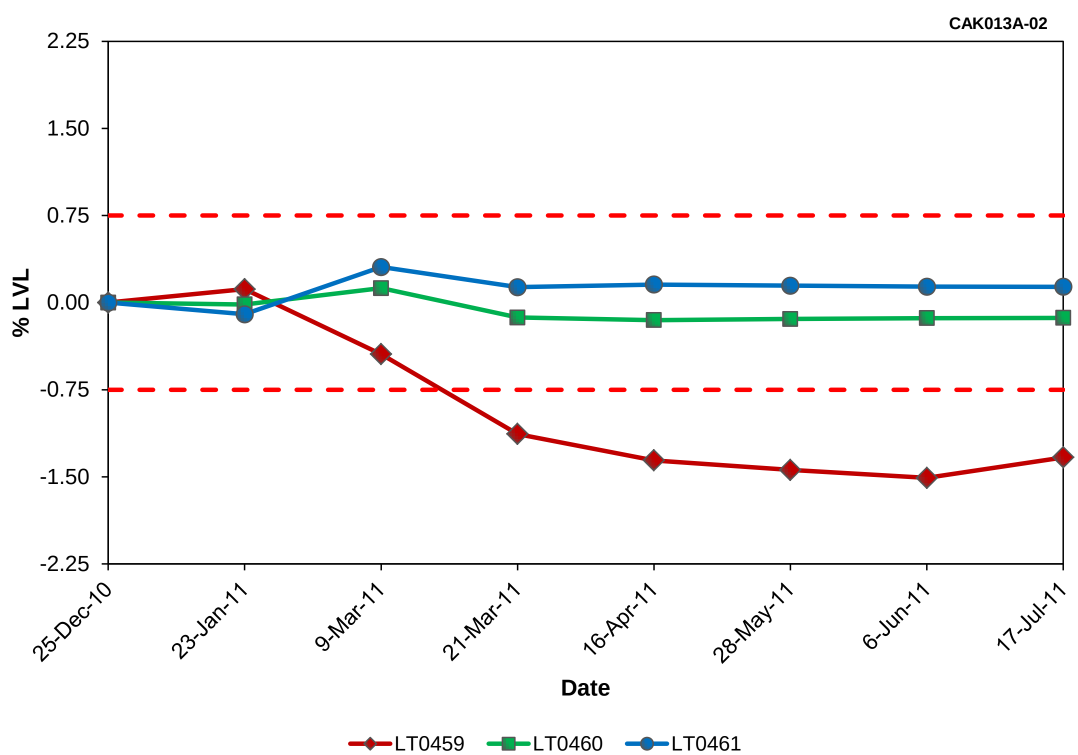


Figure 3.10 PRESSURIZER LEVEL Steady-State Drift at Farley Unit 1 (Cycle 24)

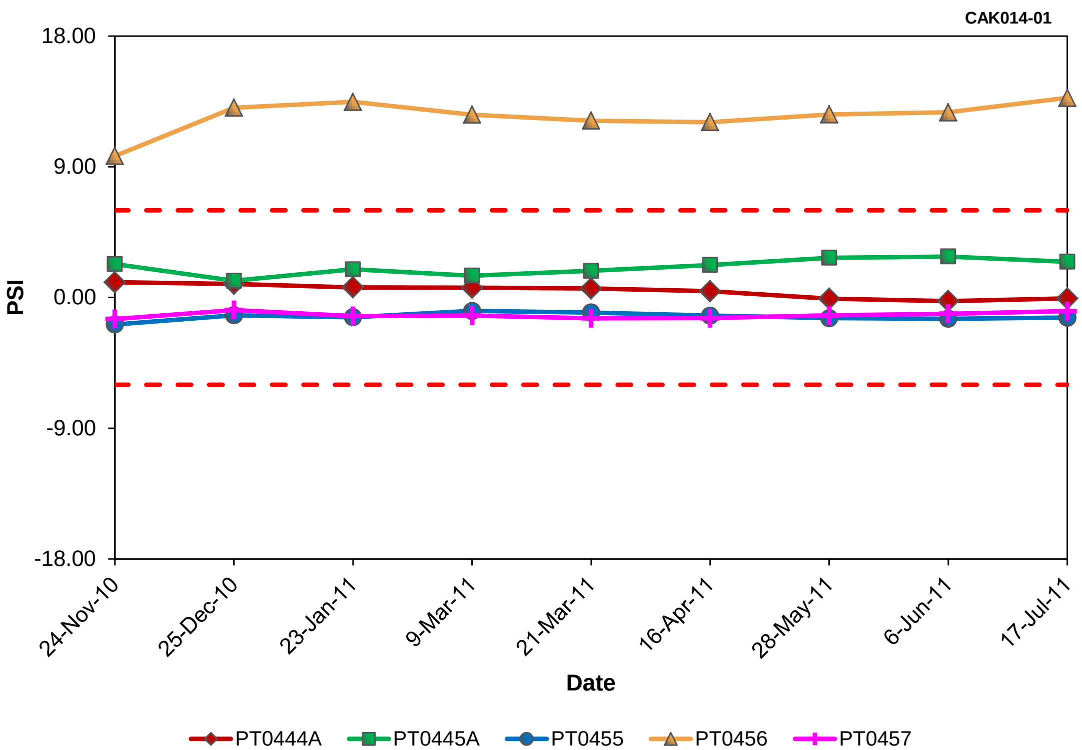


Figure 3.11 PRESSURIZER PRESSURE Steady-State Deviation at Farley Unit 1 (Cycle 24)

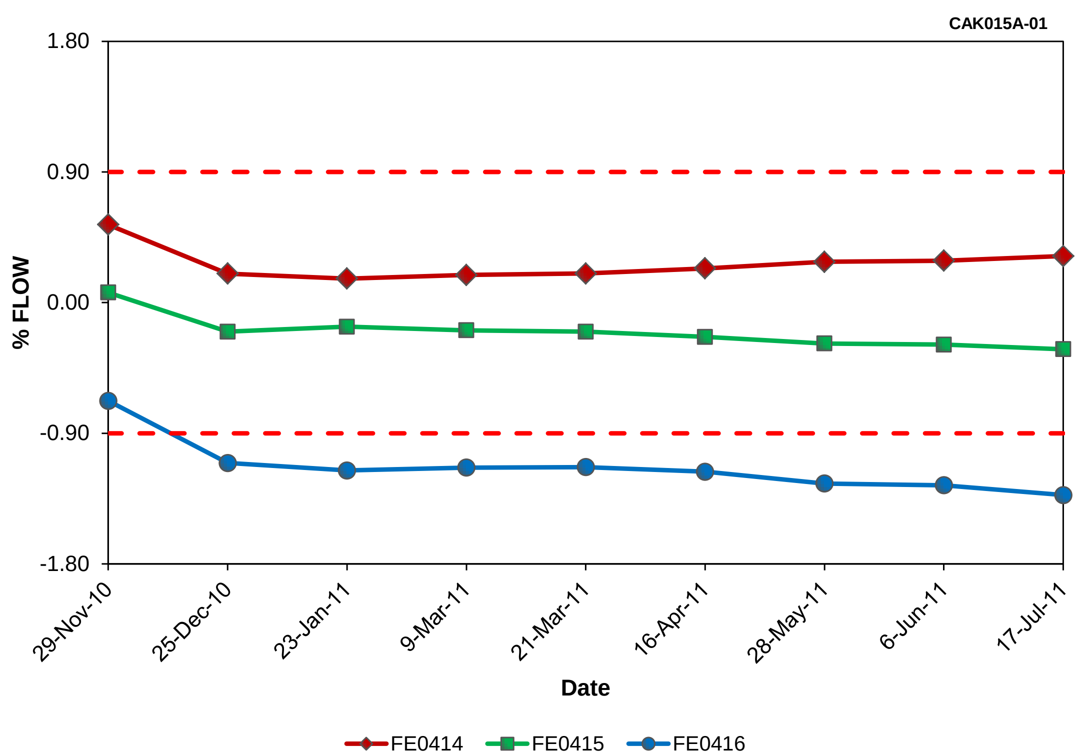


Figure 3.12 RCS LOOP A FLOW Steady-State Deviation at Farley Unit 1 (Cycle 24)

3.4 Farley Unit 2 Cycle 20

The OLM analysis for Farley Unit 2 Cycle 20 includes 8 months of steady-state data between August 2009 and March 2010, shutdown transients in April 2010 and dynamic OLM data taken prior to shutdown in March 2010. Of the 61 transmitters that were analyzed during this cycle, 6 were identified with potential problems. These transmitters are listed in Table 3.4.

SG A WIDE RANGE LEVEL transmitter LT0477 exhibits low drift over the cycle as shown in the model analysis results in Figure 3.13.

SG A OUTLET PRESSURE transmitter PT0476 shows a low bias in both the steady-state data (Figure 3.14) and the shutdown data (not shown).

SG B NARROW RANGE LEVEL transmitter LT0485 exhibits a high bias in the shutdown data as shown in Figure 3.15.

Similarly to SG A Wide Range Level transmitter LT0477, SG C WIDE RANGE LEVEL transmitter LT0497 shows a low drift over the cycle which causes it to exceed its lower OLM acceptance criteria (Figure 3.16).

PRESSURIZER LEVEL transmitter LT0461 shows a low bias in the shutdown data (Figure 3.17).

Although PRESSURIZER PRESSURE transmitters PT0455 and PT0457 show a low drift during the middle of the cycle (Figure 3.18), they are both within their OLM acceptance limits in the shutdown data (Figure 3.19) and are considered to pass. As will be shown in the next section, these two transmitters also exhibit this low drift during the next cycle, which has prompted SNOC engineers to postulate that these transmitters are showing signs of environmental effects.

RCS LOOP A FLOW transmitter FE0416 exhibits a low bias throughout the cycle (Figure 3.20).

Dynamic OLM data taken on the steam flow, narrow range SG levels and feedwater flow transmitters in Unit 2 during this cycle did not reveal any problems with the dynamic characteristics of the transmitters.

Table 3.4 Farley Unit 2 Transmitters with Potential Problems (Cycle 20)

Item	Tagname	Service	Comment
1	LT0477	SG A WIDE RANGE LEVEL	Drift over cycle.
2	PT0476	SG A OUTLET PRESSURE	Low bias.
3	LT0485	SG B NARROW RANGE LEVEL	High bias in shutdown data.
4	LT0497	SG C WIDE RANGE LEVEL	Drift over cycle.
5	LT0461	PRESSURIZER LEVEL	Low bias in shutdown data.
6	FE0416	RCS LOOP A FLOW	Low bias.

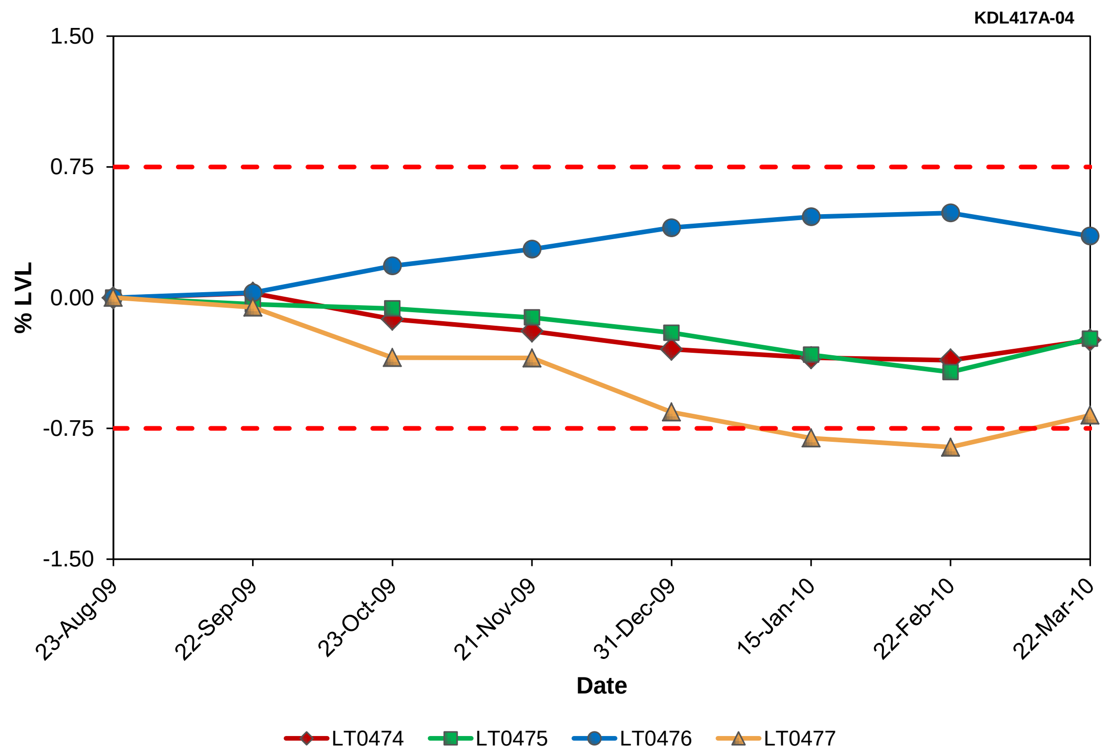


Figure 3.13 SG A LEVEL Model Analysis at Farley Unit 2 (Cycle 20)

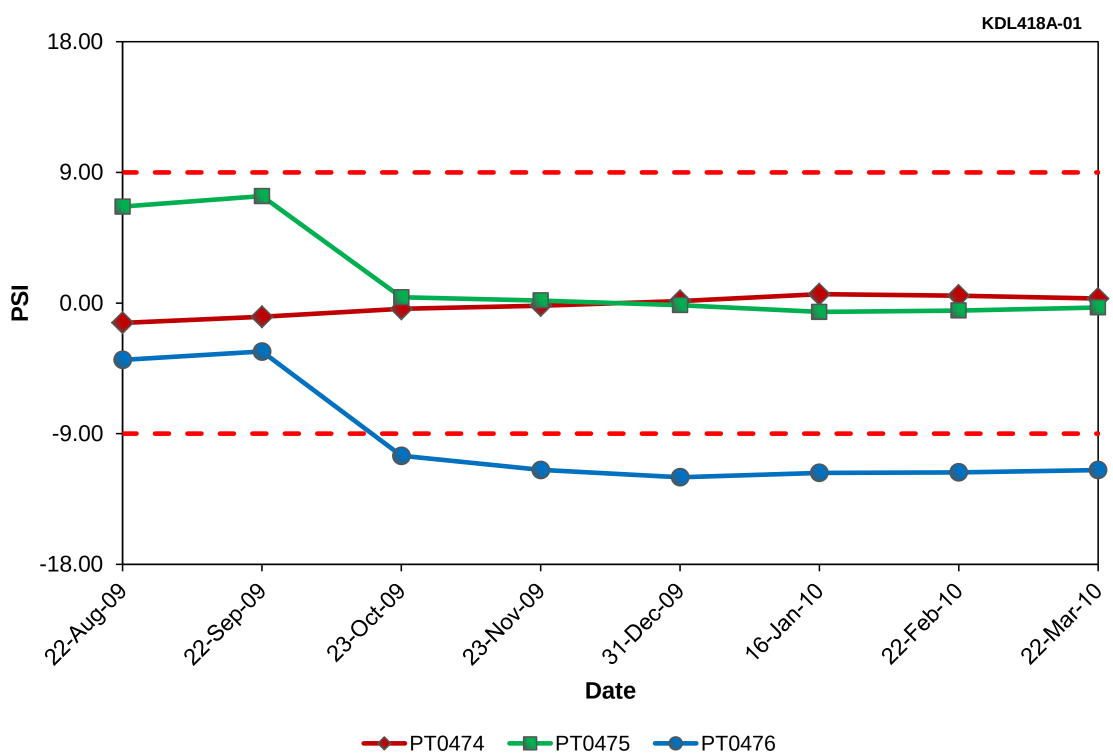


Figure 3.14 SG A OUTLET PRESSURE Steady-State Deviation at Farley Unit 2 (Cycle 20)

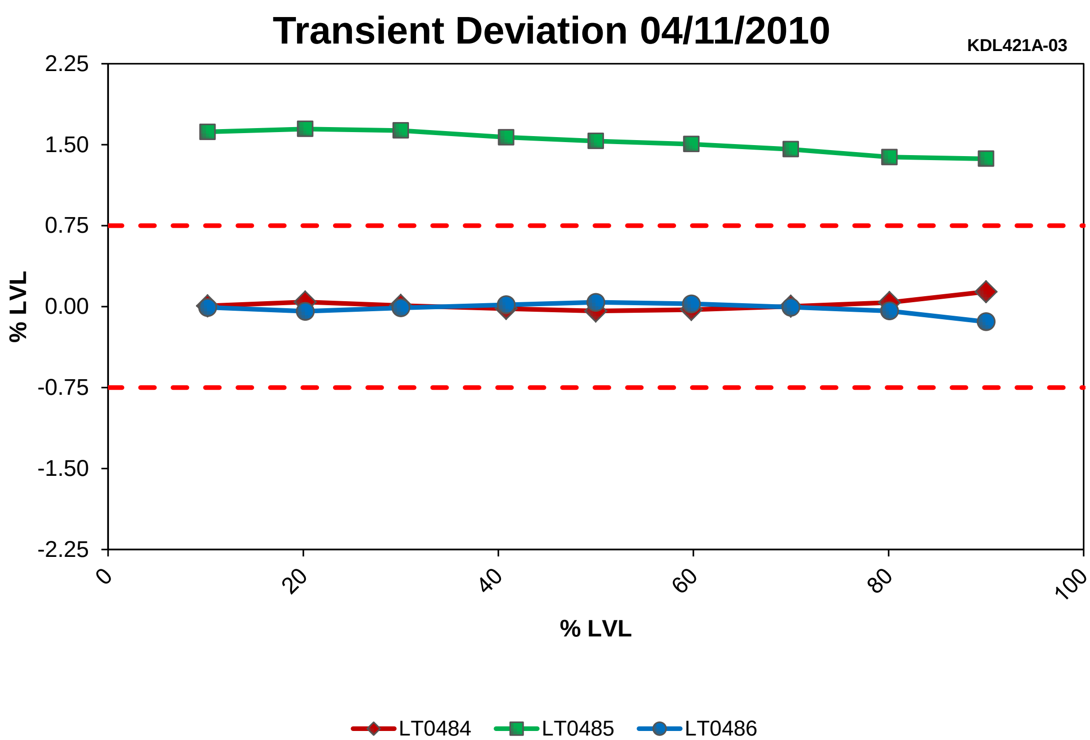


Figure 3.15 SG B LEVEL Transient Deviation at Farley Unit 2 (Cycle 20)

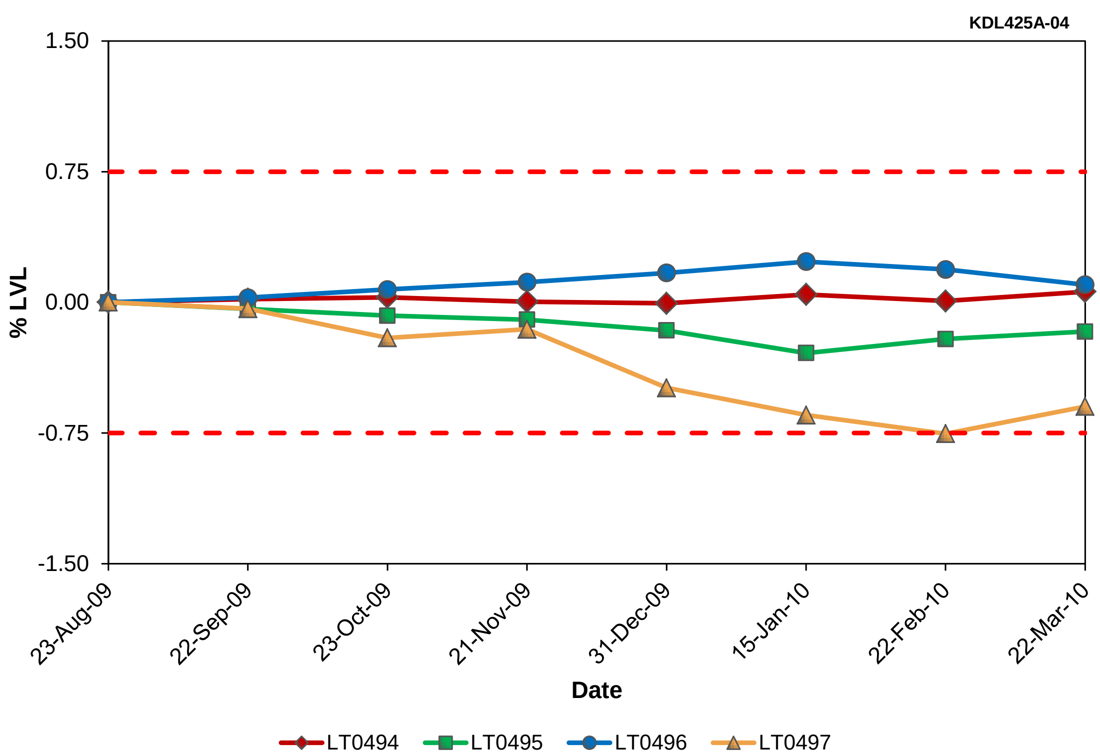


Figure 3.16 SG C LEVEL Model Analysis at Farley Unit 2 (Cycle 20)

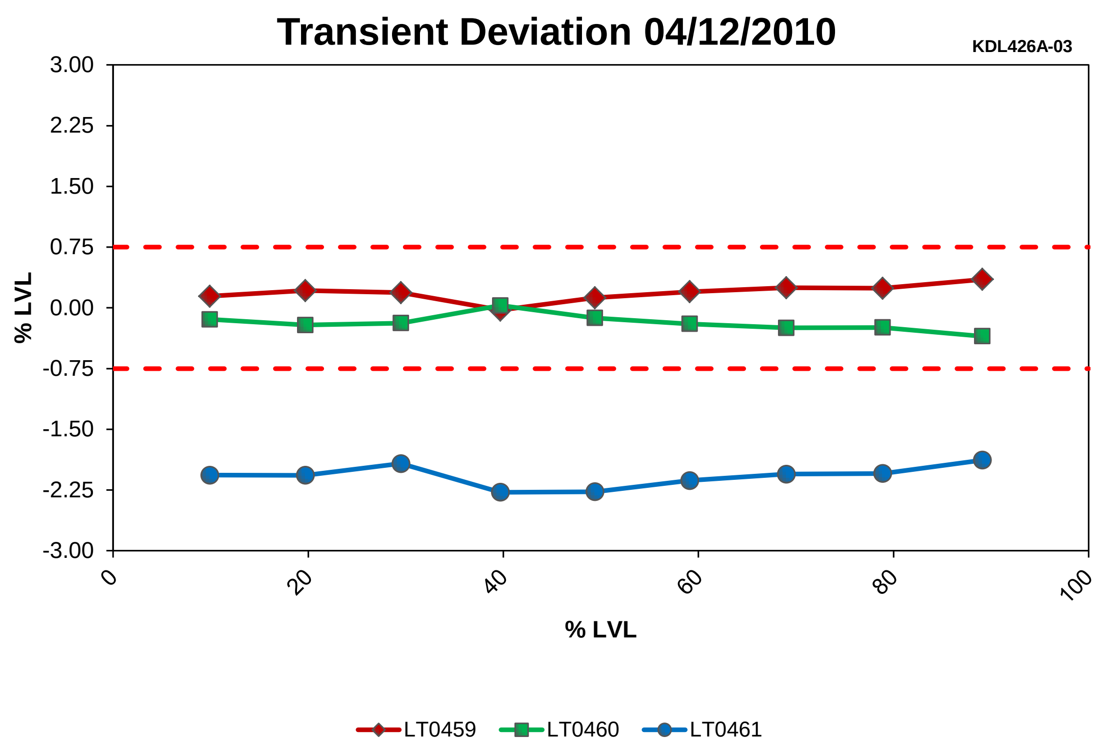


Figure 3.17 PRESSURIZER LEVEL Transient Deviation at Farley Unit 2 (Cycle 20)

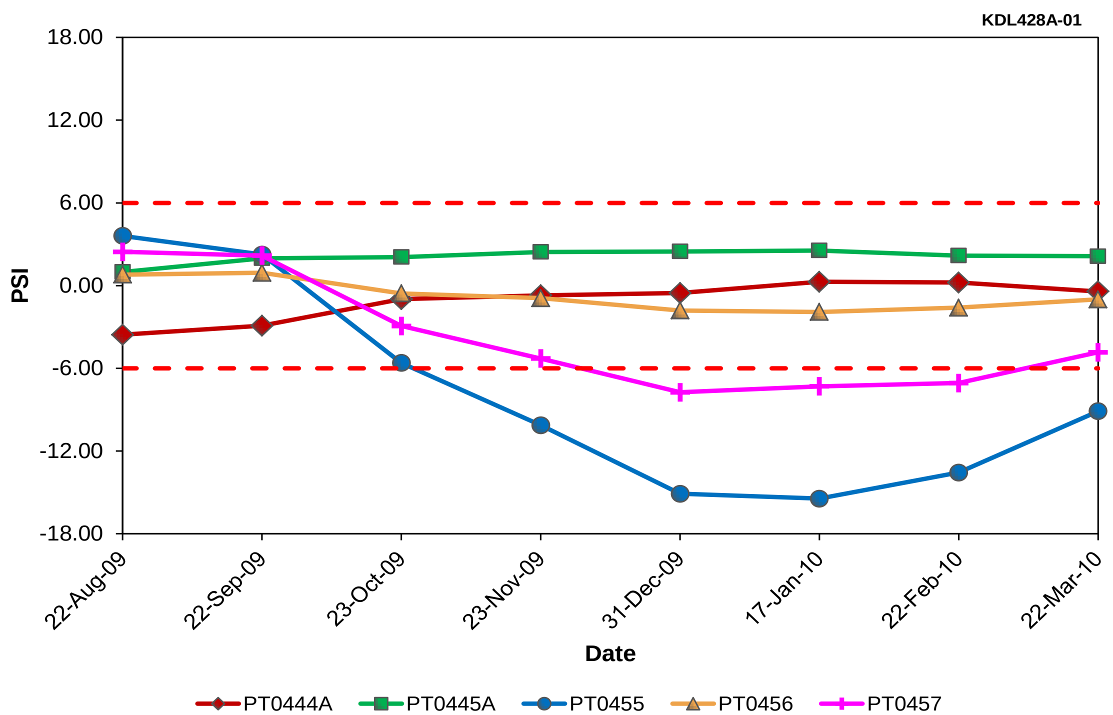


Figure 3.18 PRESSURIZER PRESSURE Steady-State Deviation at Farley Unit 2 (Cycle 20)

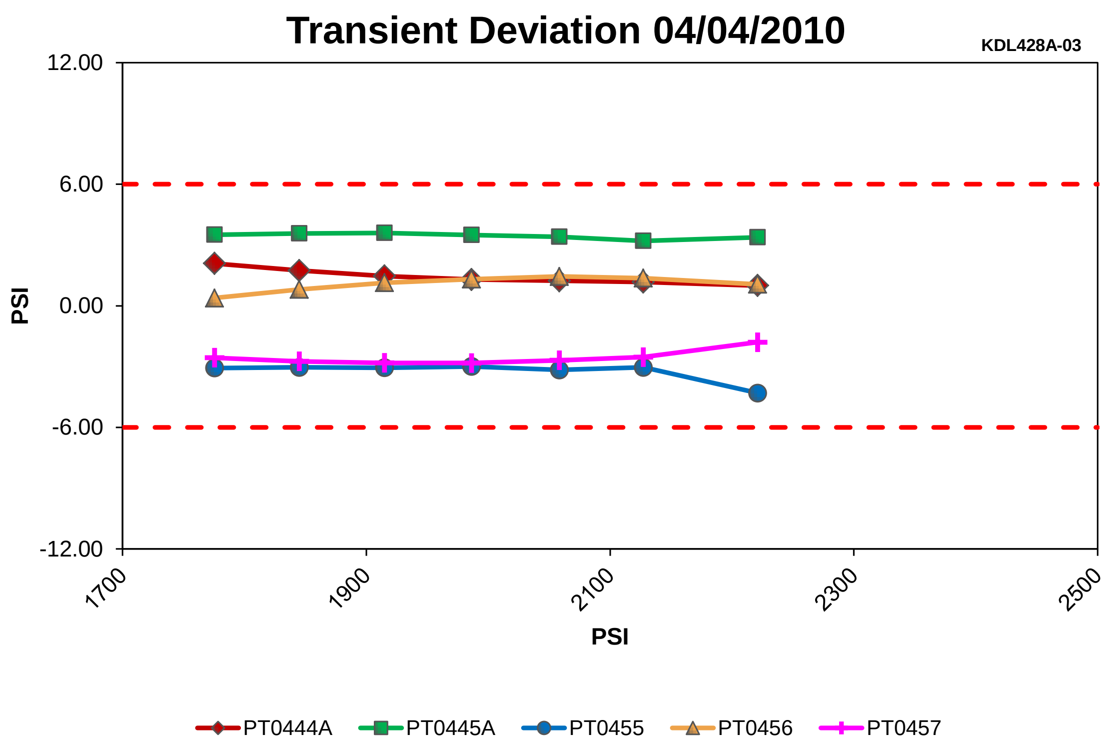


Figure 3.19 PRESSURIZER PRESSURE Transient Deviation at Farley Unit 2 (Cycle 20)

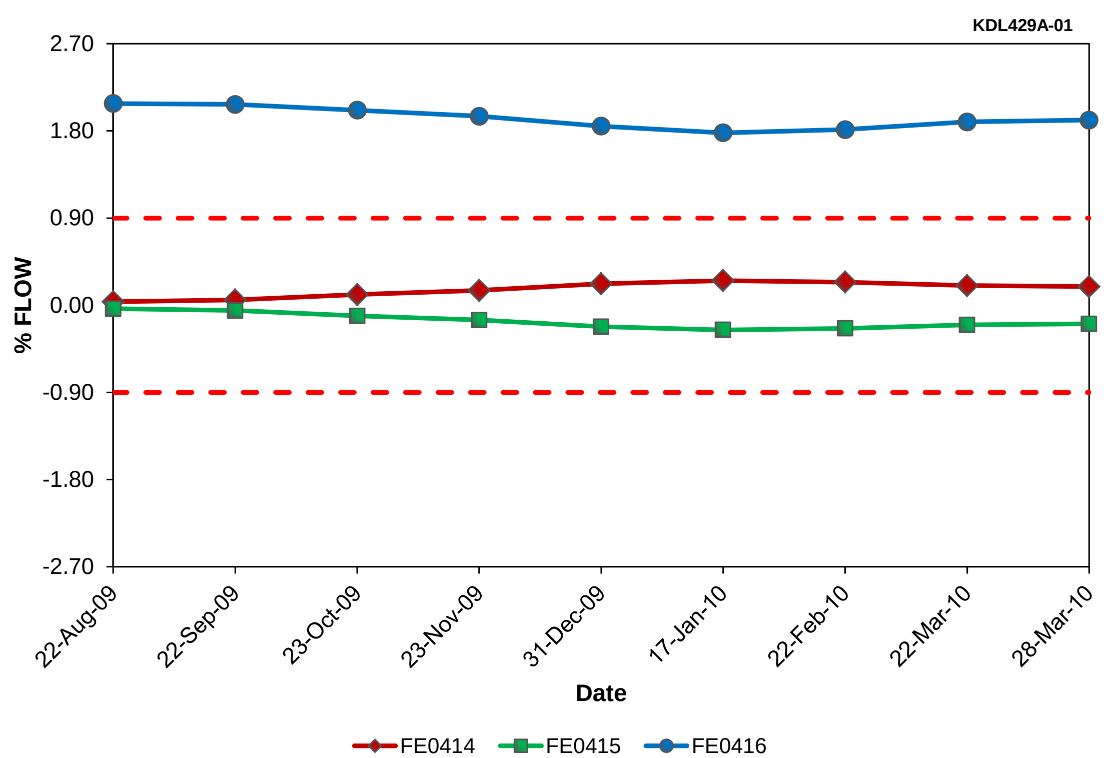


Figure 3.20 RCS LOOP A FLOW Steady-State Deviation at Farley Unit 2 (Cycle 20)

3.5 Farley Unit 2 Cycle 21

The OLM analysis for Farley Unit 2 Cycle 21 includes startup data in May 2010, 18 points of steady-state data between June 2010 and July 2010, and dynamic OLM data taken just after startup in July 2010. Of the 61 transmitters that were analyzed during this cycle, 6 were identified with potential problems. These transmitters are listed in Table 3.5.

SG A LEVEL NARROW RANGE transmitter LT0476 drifts high in the middle of the cycle but drifts back to normal later in the cycle (Figure 3.21). Although this transmitter is currently passing, it should be watched carefully.

SG C STEAM FLOW transmitter FE0495B drifts low during the cycle and exceeds its OLM acceptance criteria limits (Figure 3.22).

SG C NARROW RANGE LEVEL transmitter LT0496 exhibits a low bias during the startup transient (Figure 3.23).

PRESSURIZER LEVEL transmitter LT0459 exhibits a high bias during the cycle (Figure 3.24).

PRESSURIZER PRESSURE transmitter PT0455 exhibits high drift in the cycle until late January 2011, at which time, plant personnel indicated that it was re-calibrated. Since the calibration between January and March 2011, this transmitter has drifted slightly and should still be watched. Similar to the previous cycle, transmitters PT0455 and PT0457 exhibit low drift during the cycle until they come back in with the rest of the transmitters, indicating a potential environmental effect on these two transmitters (Figure 3.25).

RCS LOOP C FLOW transmitter FE0434 exhibits a low bias throughout the cycle (Figure 3.26).

Dynamic OLM data taken on the steam flow, narrow range SG levels and feedwater flow transmitters in Unit 2 during this cycle did not reveal any problems with the dynamic characteristics of the transmitters.

Table 3.5 Farley Unit 2 Transmitters with Potential Problems (Cycle 21)

Item	Tagname	Service	Comment
1	LT0476	SG A NARROW RANGE LEVEL	Drift high over cycle.
2	FE0495B	SG C STEAM FLOW	Low drift during cycle.
3	LT0496	SG C NARROW RANGE LEVEL	Low bias in startup transient.
4	LT0459	PRESSURIZER LEVEL	High bias.
5	PT0455	PRESSURIZER PRESSURE	Drift High.
6	FE0434	RCS LOOP C FLOW	Low bias.

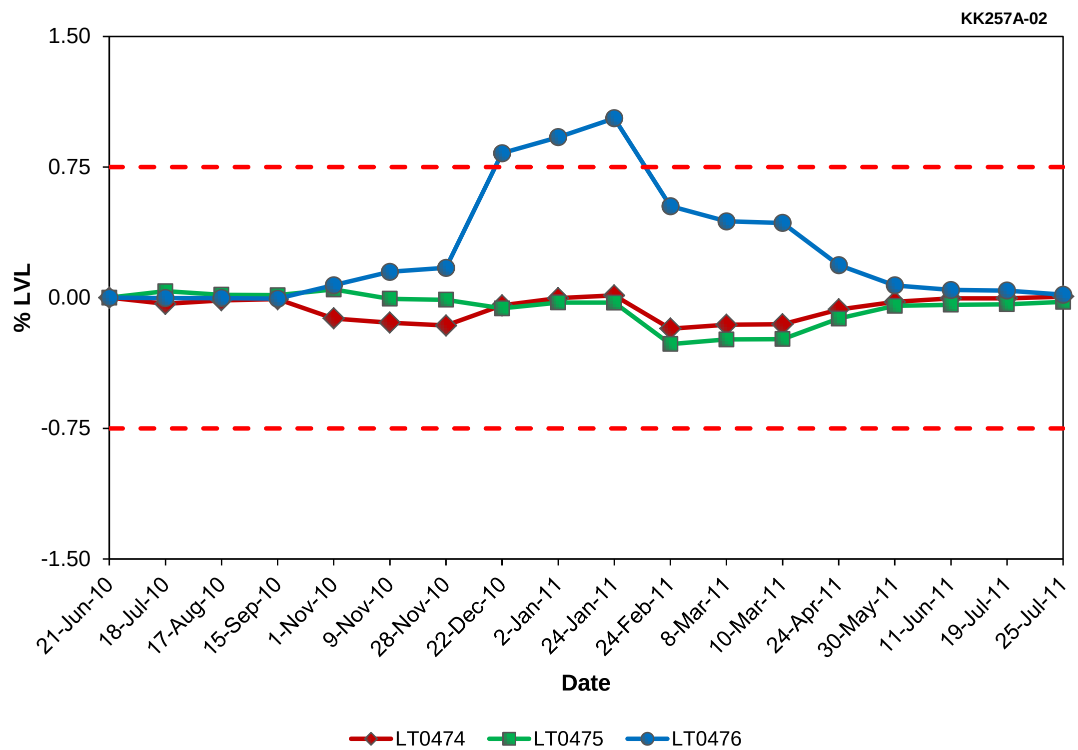


Figure 3.21 SG A LEVEL Steady-State Drift at Farley Unit 2 (Cycle 21)

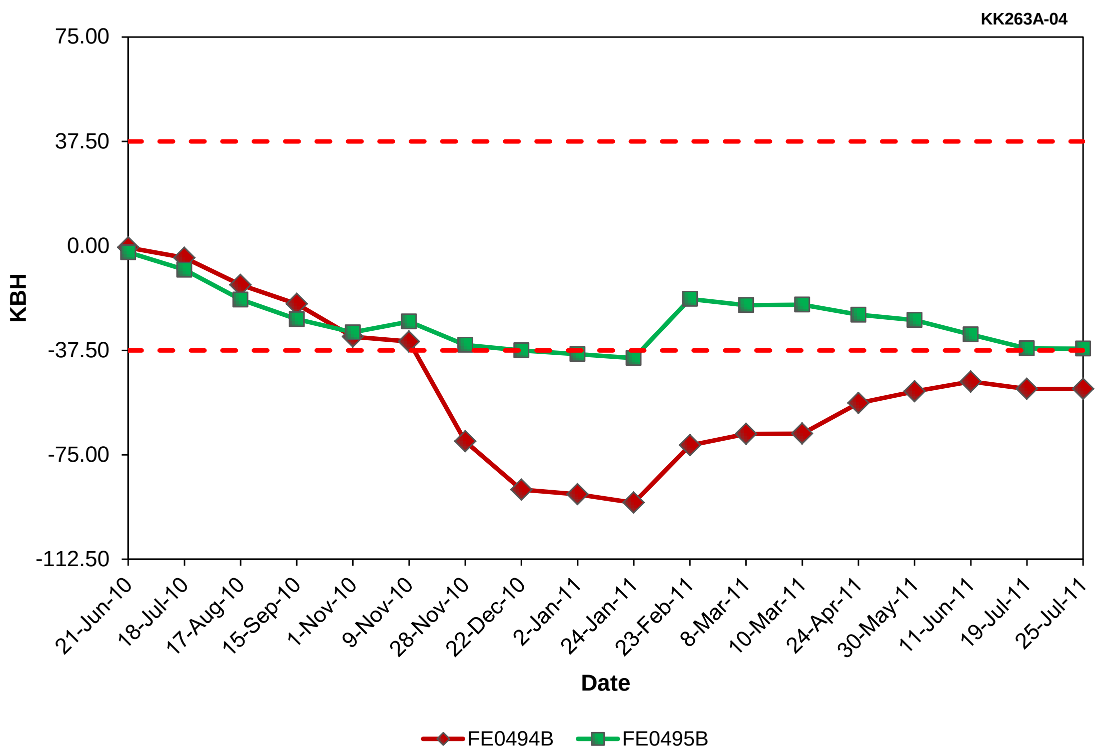


Figure 3.22 SG C STEAM FLOW Model Analysis at Farley Unit 2 (Cycle 21)

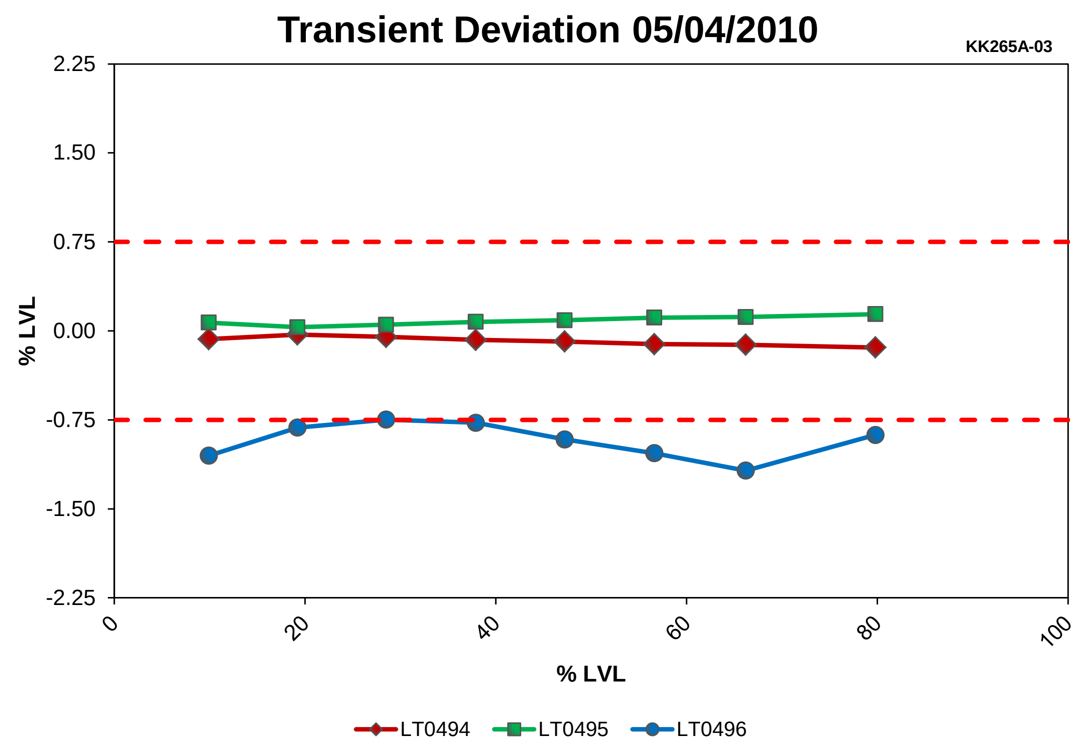


Figure 3.23 SG C LEVEL Transient Deviation at Farley Unit 2 (Cycle 21)

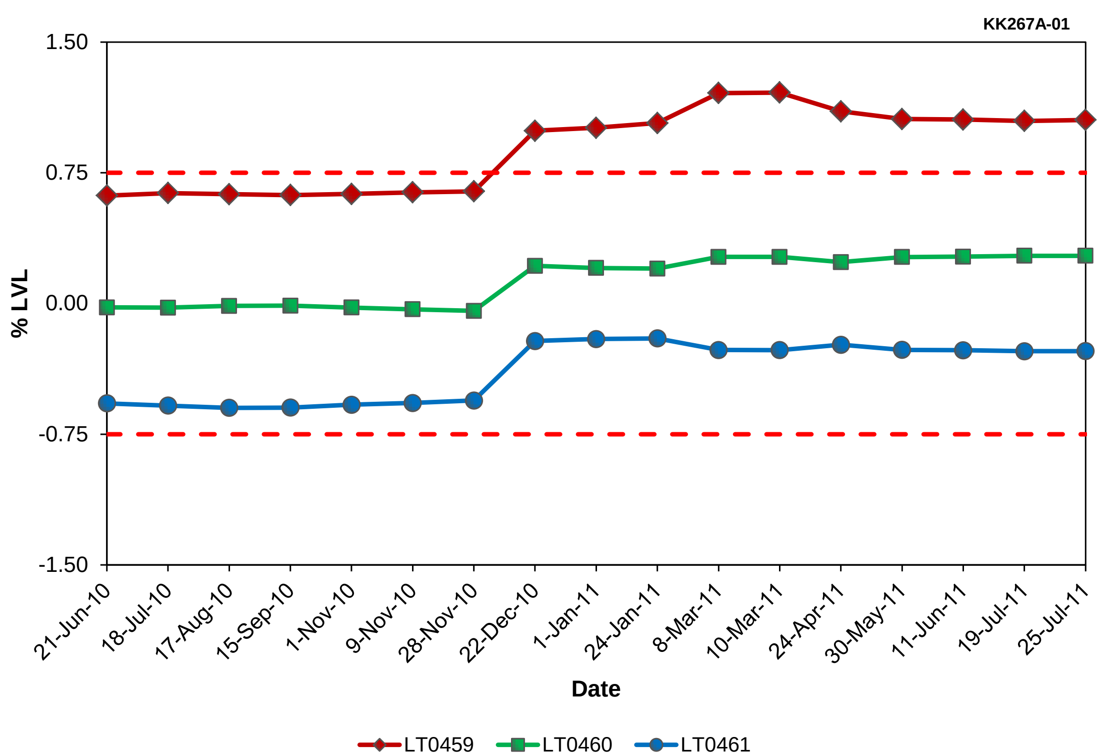


Figure 3.24 PRESSURIZER LEVEL Steady-State Deviation at Farley Unit 2 (Cycle 21)

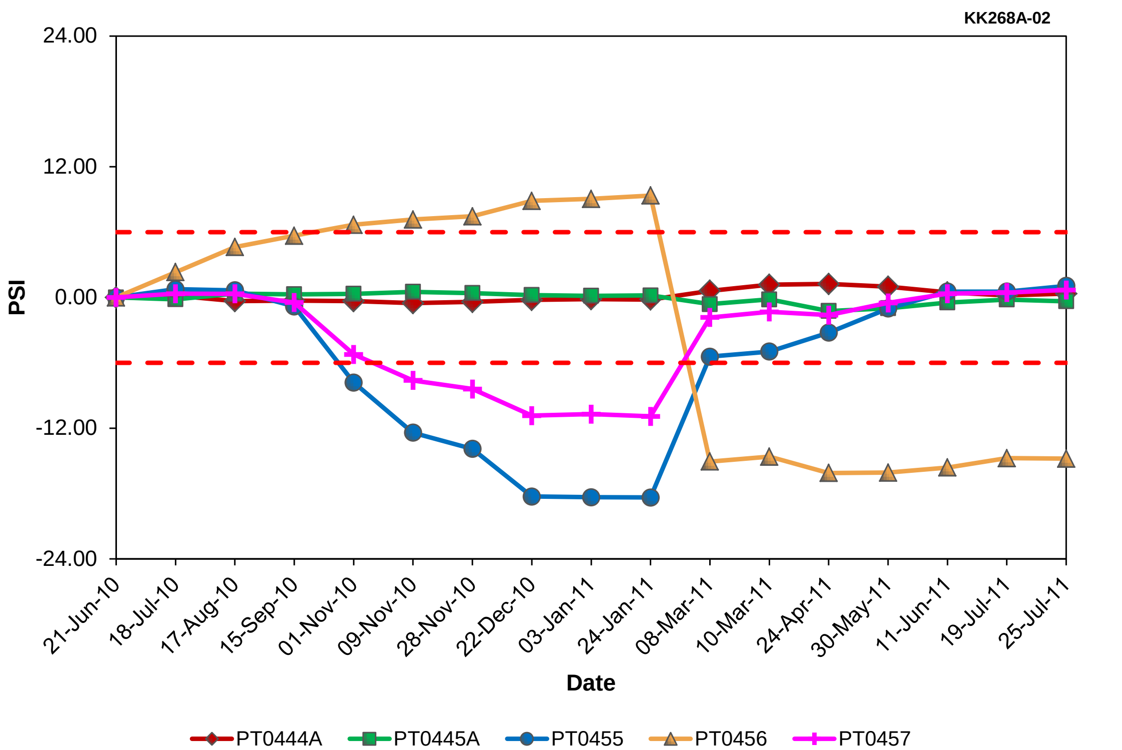


Figure 3.25 PRESSURIZER PRESSURE Steady-State Drift at Farley Unit 2 (Cycle 21)

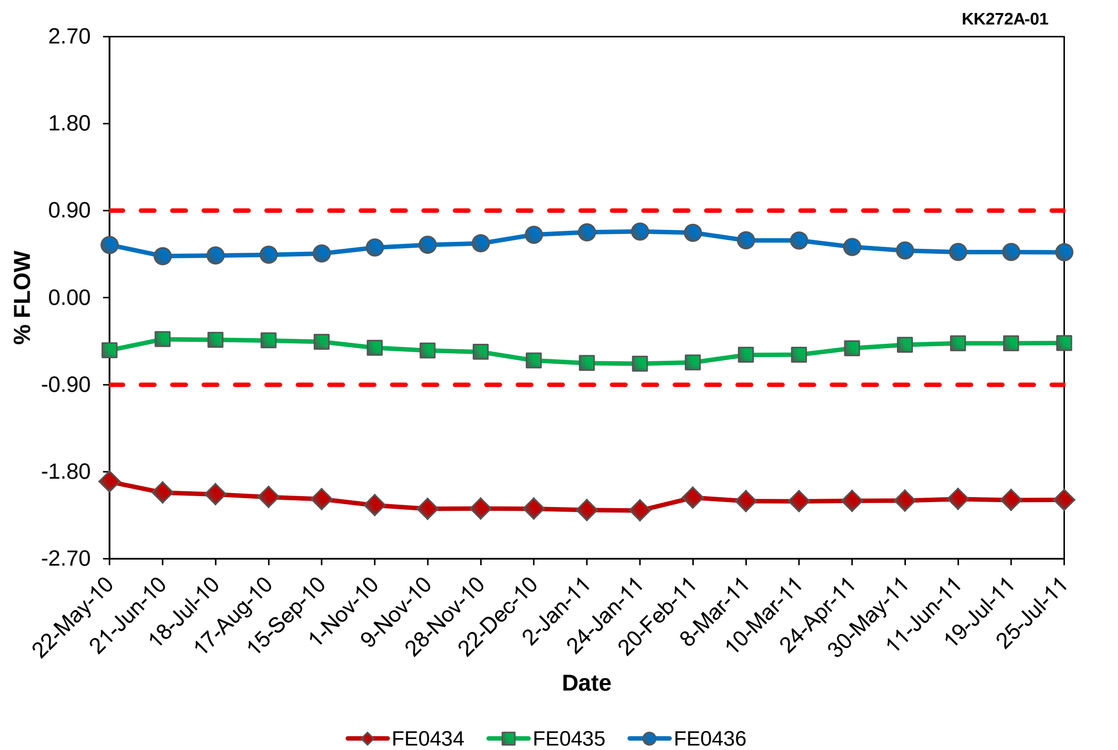


Figure 3.26 RCS LOOP C FLOW Steady-State Deviation at Farley Unit 2 (Cycle 21)

3.6 North Anna Unit 1 Cycle 20

The OLM analysis for North Anna Unit 1 Cycle 20 includes 13 months of steady-state data from January 2008 to March 2009. Of the 52 transmitters that were analyzed during this cycle, 2 were identified with potential problems. These transmitters are listed in Table 3.6.

TURBINE FIRST STAGE PRESSURE transmitters P0398A and P0399A appear to drift high during the cycle in the analytical modeling results as shown in Figure 3.27. However, the apparent drift in the modeling results may be the result of differences in the training data at the start of the cycle and changes in the mean process value over the cycle (Figure 3.28) instead of sensor drift.

3.7 North Anna Unit 1 Cycle 21

The OLM analysis for North Anna Unit 1 Cycle 21 includes startup data from April 2009 and 15 months of steady-state data from May 2009 to August 2010. Of the 52 transmitters that were analyzed during this cycle, none of the transmitters exceeded their OLM acceptance criteria in the redundant sensor analysis results (using averaging techniques). However, 16 of the transmitters exceeded their OLM acceptance criteria in the modeling analysis (Table 3.7). These transmitters are believed to have exceeded their OLM acceptance criteria in the modeling analysis as a result of process changes from the beginning of the cycle (when the models were trained) to the end of the cycle. Figures 3.29 through 3.36 show results from the modeling analysis of these transmitters over Cycle 21.

3.8 North Anna Unit 1 Cycle 22

The OLM analysis for North Anna Unit 1 Cycle 22 includes 6 months of steady-state data from November 2010 to April 2011. Of the 52 transmitters that were analyzed during this cycle, none of the transmitters exceeded their OLM acceptance criteria in the redundant sensor analysis results (using averaging techniques). However, 2 of the SG C OUTLET PRESSURE transmitters exceeded their OLM acceptance criteria in the modeling analysis (Table 3.8). As in previous cycles, these transmitters are believed to have exceeded their OLM acceptance criteria in the modeling analysis as a result of process changes throughout the cycle. Figure 3.37 shows the results from the modeling analysis of the SG C OUTLET PRESSURE transmitters in Cycle 22.

Table 3.6 North Anna Unit 1 Transmitters with Potential Problems (Cycle 20)

Item	Tagname	Service	Comment
1	P0398A	TURBINE FS PRESSURE	Drift high over cycle.
2	P0399A	TURBINE FS PRESSURE	Drift high over cycle

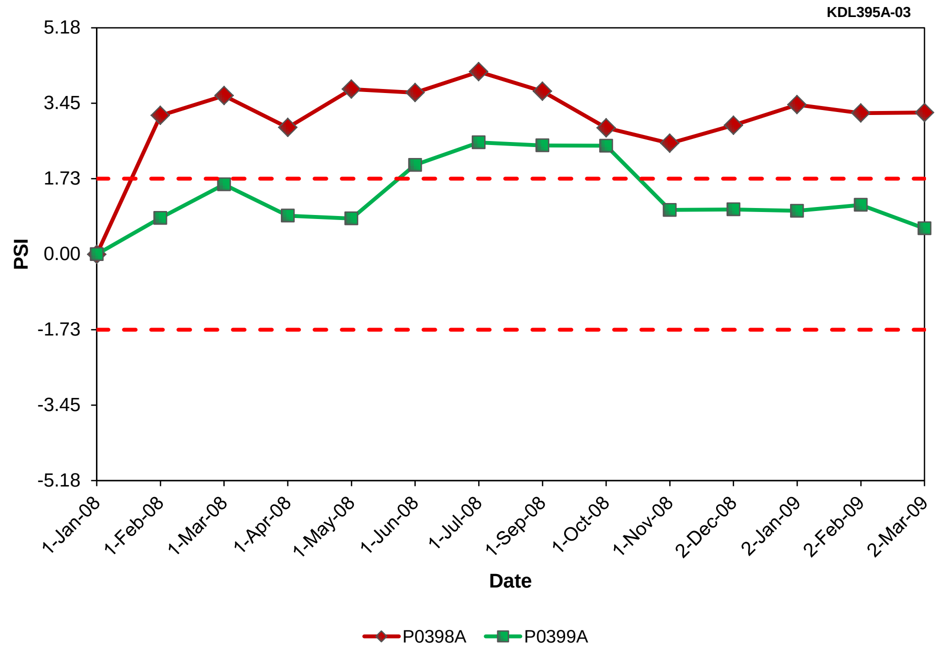


Figure 3.27 TURBINE FS PRESSURE Model Analysis At North Anna Unit 1 (Cycle 20)

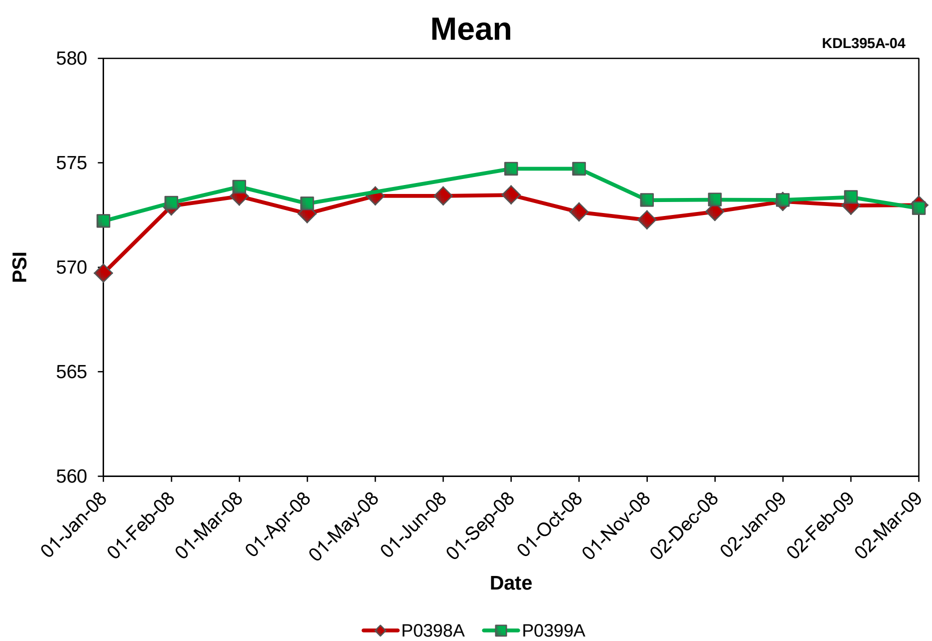


Figure 3.28 TURBINE FS PRESSURE Mean Values At North Anna Unit 1 (Cycle 20)

Table 3.7 North Anna Unit 1 Transmitters Exceeding Modeling Limits (Cycle 21)

Item	Tagname	Service	Comment
1	F1MS001A	SG A STEAM FLOW	Process change
2	F1MS002A	SG A STEAM FLOW	Process change
3	F1FW004A	FW FLOW TO SG A	Process change
4	F1FW005A	FW FLOW TO SG A	Process change
5	P1MS001A	SG A OUTLET PRESSURE	Process change
6	P1MS002A	SG A OUTLET PRESSURE	Process change
7	P1MS003A	SG A OUTLET PRESSURE	Process change
8	F1MS004A	SG B STEAM FLOW	Process change
9	P1MS004A	SG B OUTLET PRESSURE	Process change
10	P1MS005A	SG B OUTLET PRESSURE	Process change
11	P1MS006A	SG B OUTLET PRESSURE	Process change
12	F1MS005A	SG C STEAM FLOW	Process change
13	F1MS006A	SG C STEAM FLOW	Process change
14	P1MS007A	SG C OUTLET PRESSURE	Process change
15	P0398A	TURBINE FS PRESSURE	Process change
16	P0399A	TURBINE FS PRESSURE	Process change

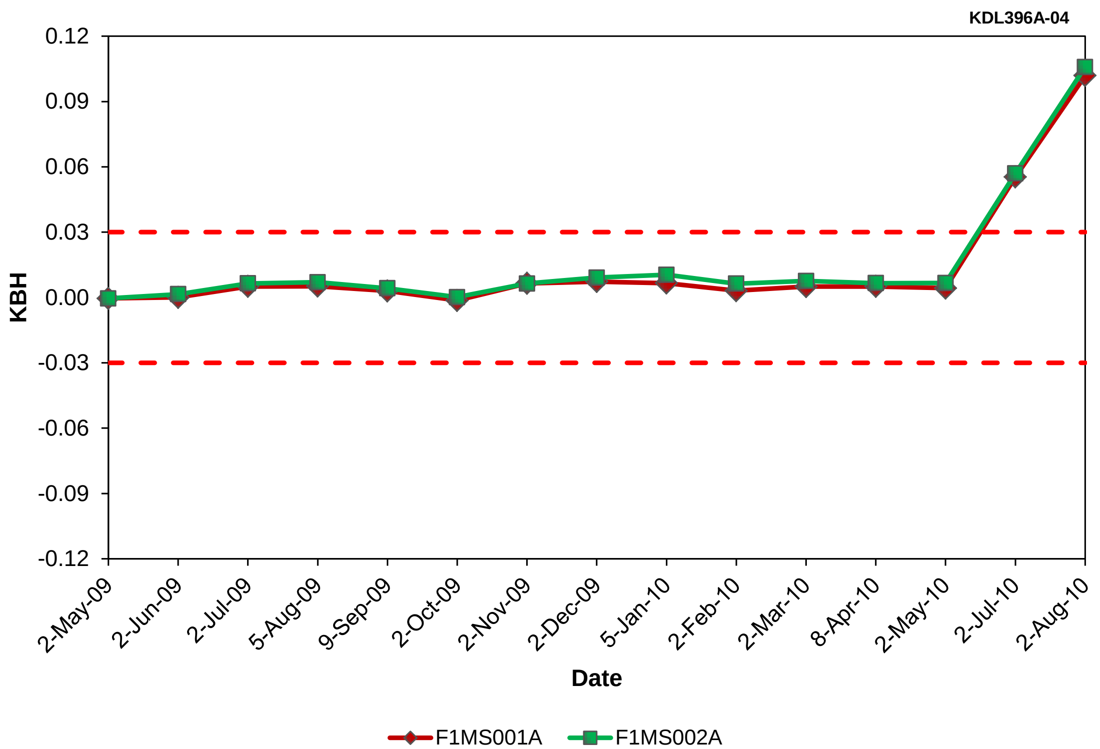


Figure 3.29 SG A STEAM FLOW Model Analysis at North Anna Unit 1 (Cycle 21)

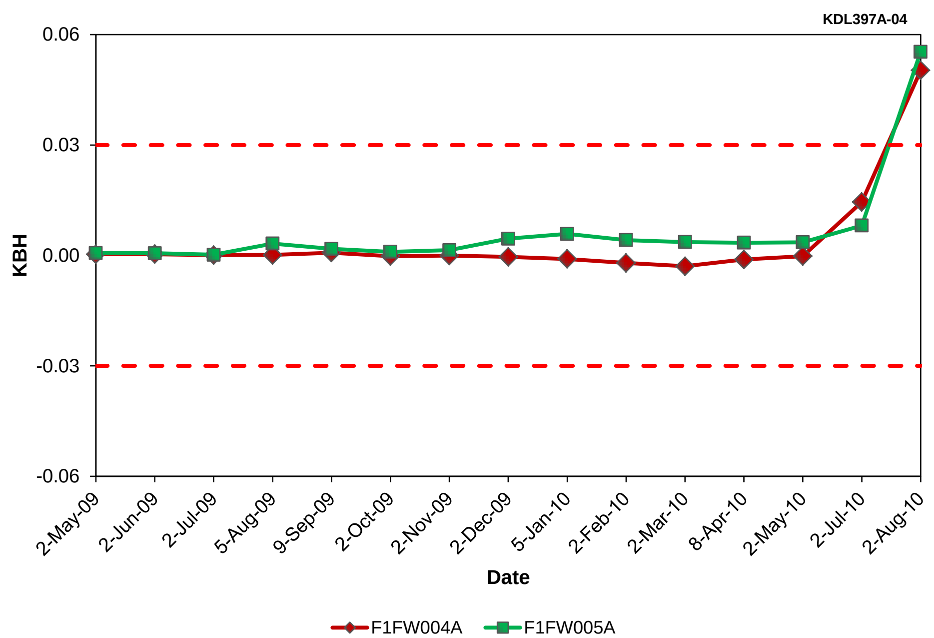


Figure 3.30 SG A FW FLOW Model Analysis at North Anna Unit 1 (Cycle 21)

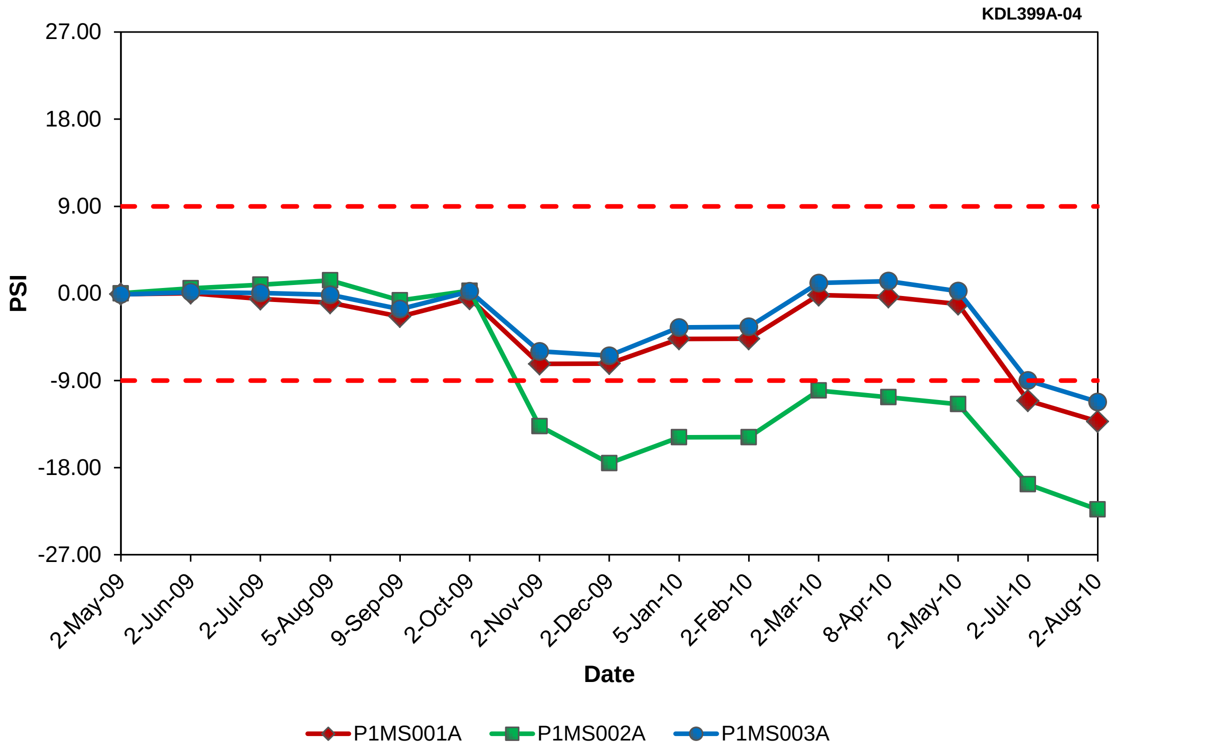


Figure 3.31 SG A OUTLET PRESSURE Model Analysis at North Anna Unit 1 (Cycle 21)

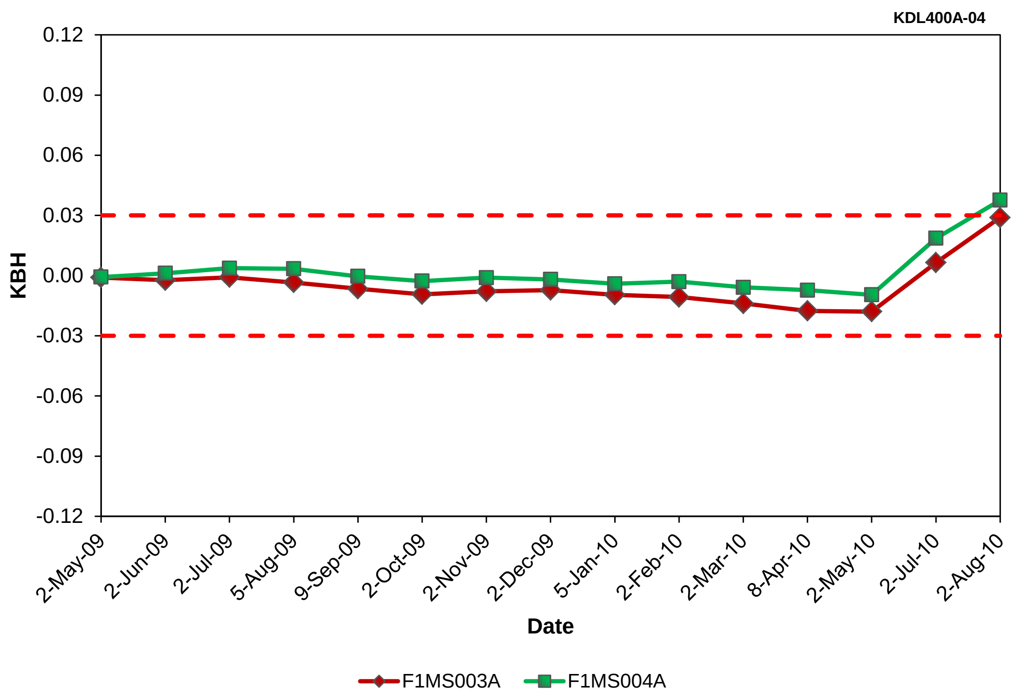


Figure 3.32 SG B STEAM FLOW Model Analysis at North Anna Unit 1 (Cycle 21)

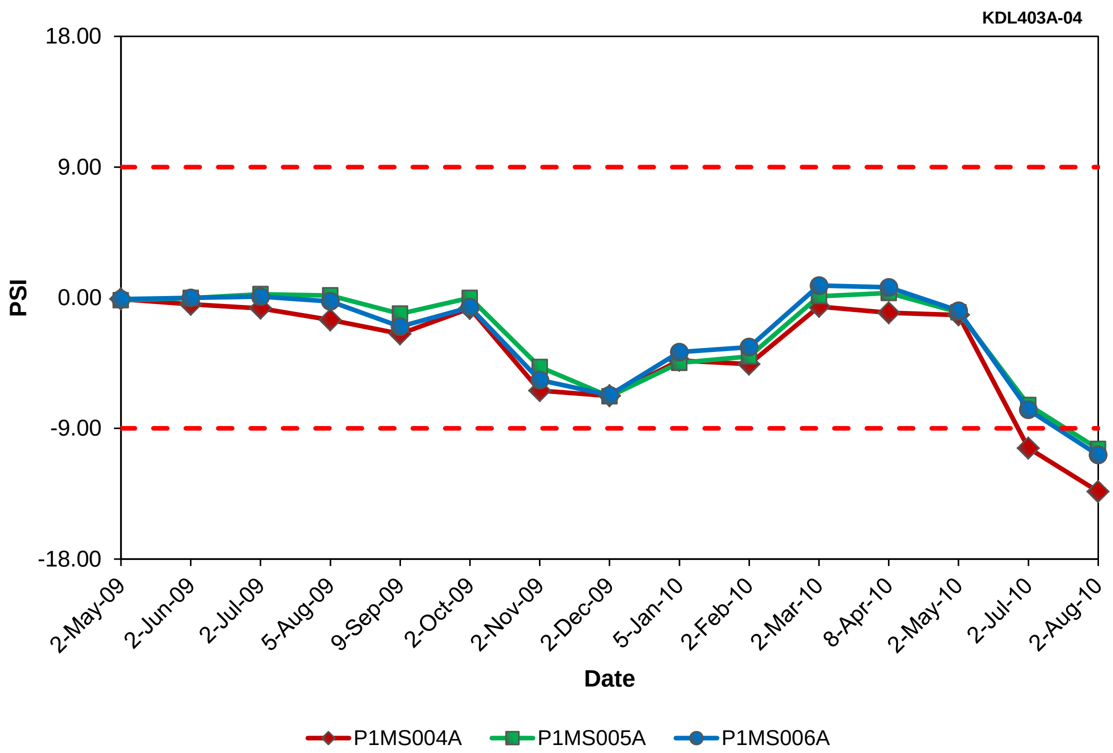


Figure 3.33 SG B OUTLET PRESSURE Model Analysis at North Anna Unit 1 (Cycle 21)

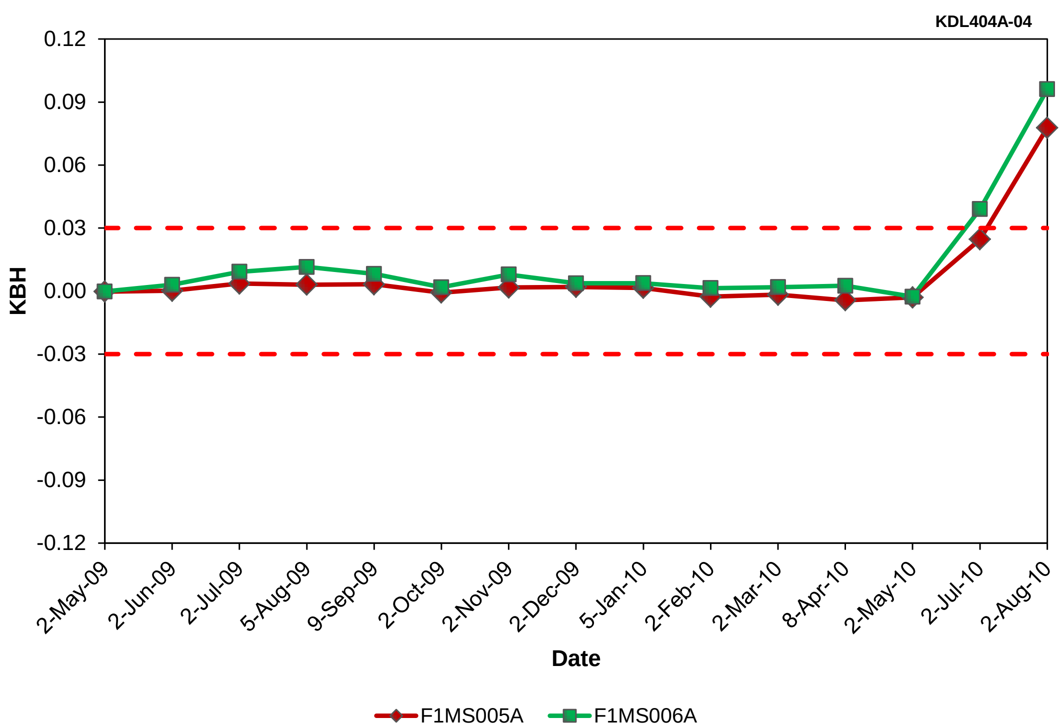


Figure 3.34 SG C STEAM FLOW Model Analysis at North Anna Unit 1 (Cycle 21)

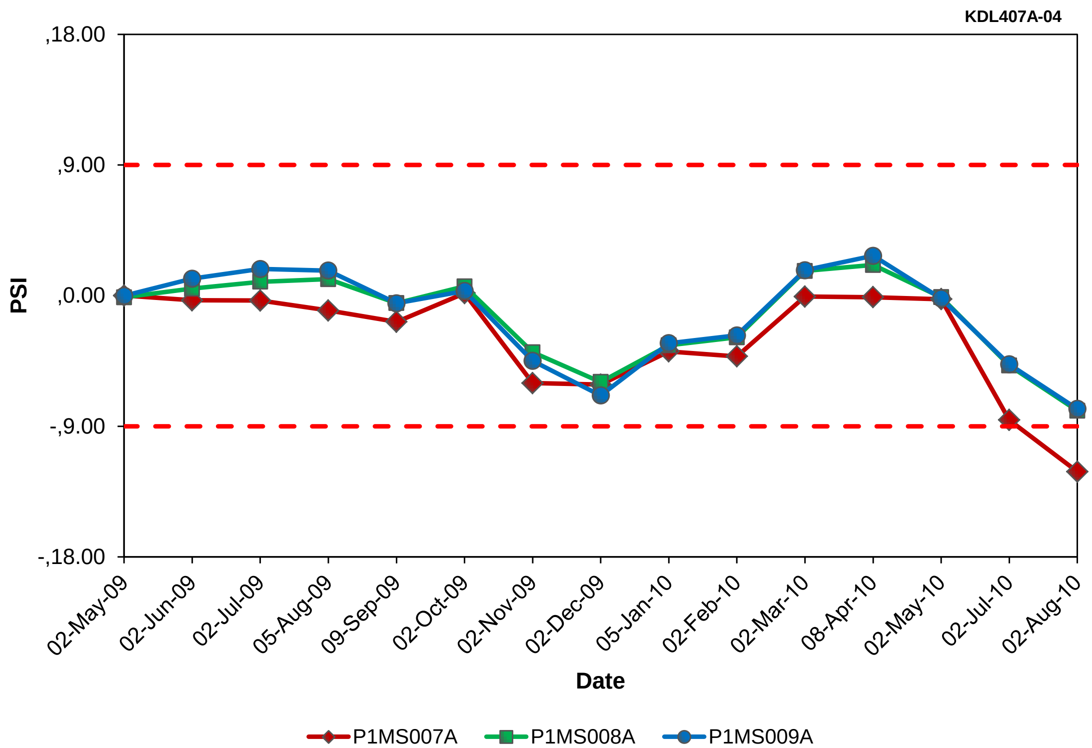


Figure 3.35 SG C OUTLET PRESSURE Model Analysis at North Anna Unit 1 (Cycle 21)

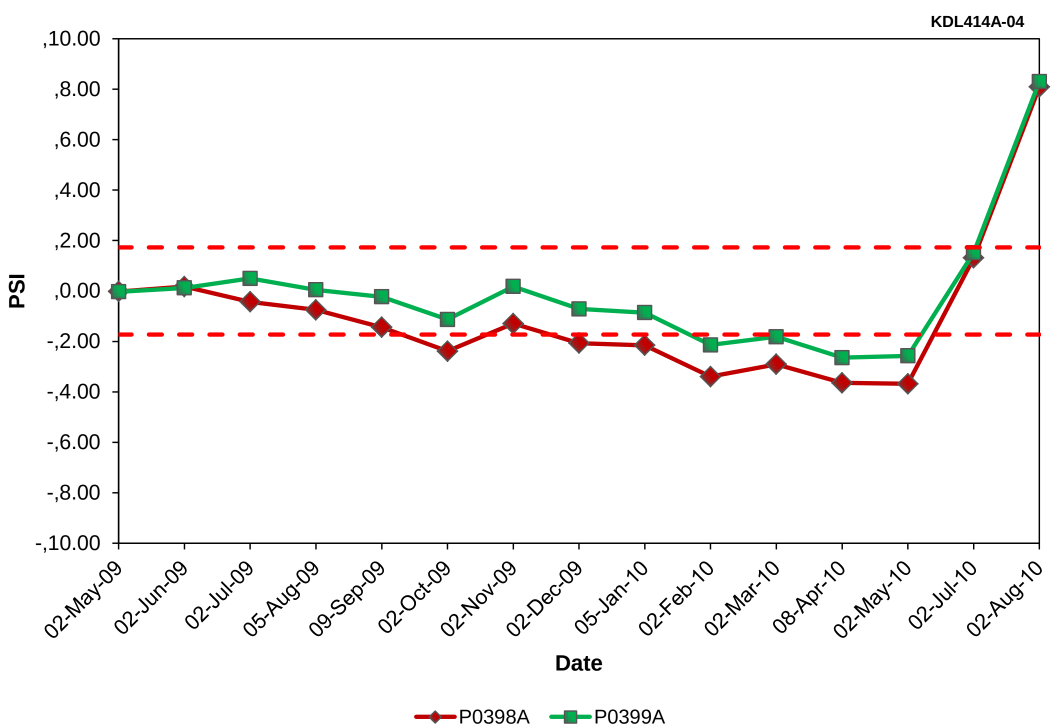


Figure 3.36 TURBINE FS PRESSURE Model Analysis at North Anna Unit 1 (Cycle 21)

Table 3.8 North Anna Unit 1 Transmitters Exceeding Modeling Limits (Cycle 22)

Item	Tagname	Service	Comment
1	P1MS008A	SG C OUTLET PRESSURE	Process change
2	P1MS009A	SG C OUTLET PRESSURE	Process change

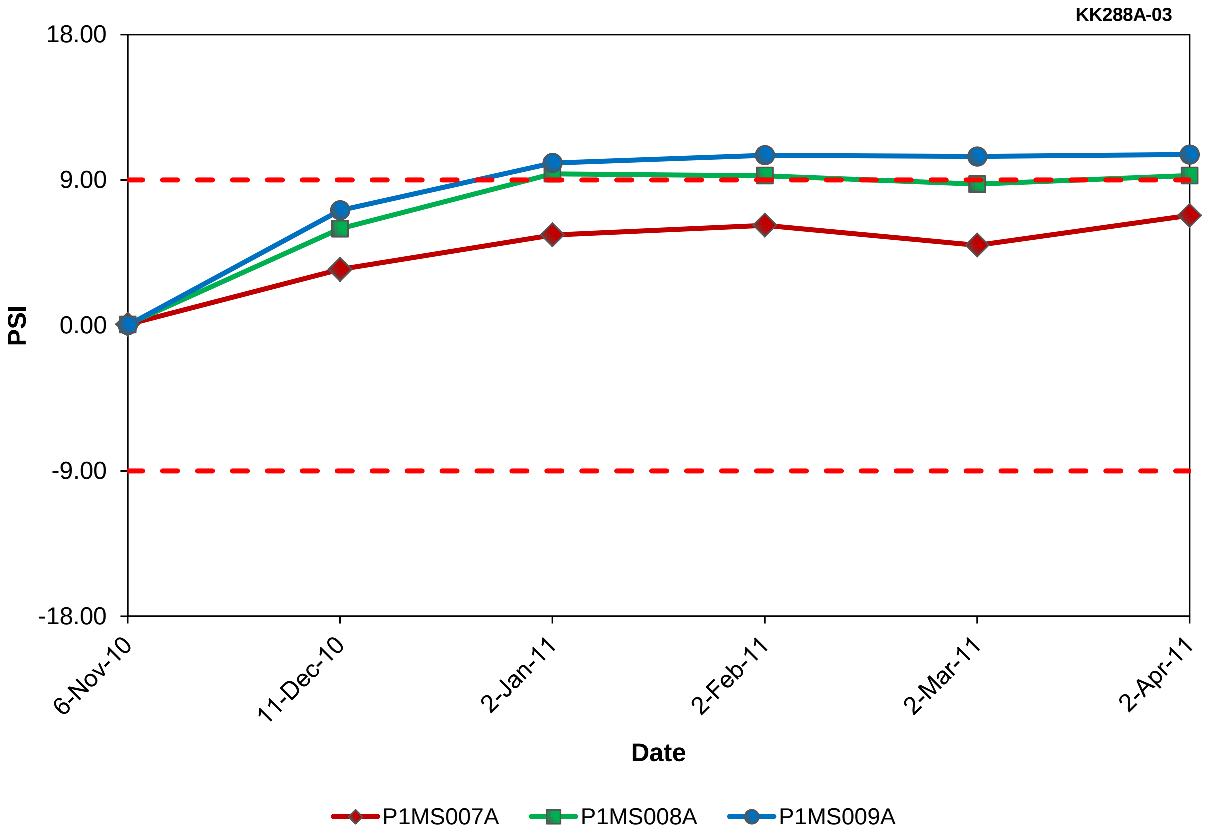


Figure 3.37 SG C OUTLET PRESSURE Model Analysis at North Anna Unit 1 (Cycle 22)

3.9 North Anna Unit 2 Cycle 21

The OLM analysis for North Anna Unit 2 Cycle 21 includes startup data from April and May 2010 (two separate startup transients) and 8 months of steady-state data from July 2010 to April 2011. Of the 52 transmitters that were analyzed during this cycle, 5 were identified with potential problems. These transmitters are listed in Table 3.9.

SG B NARROW RANGE LEVEL transmitters L2FW005A and L2FW007A appear to have significant deviations from the average that cause them to exceed their OLM acceptance criteria in the steady-state data (Figure 3.38).

Similarly, SG C STEAM FLOW transmitters F2MS005A and F2MS006A exhibit significant deviations in the steady-state data that exceed the OLM acceptance limits (Figure 3.39).

RCS LOOP C FLOW transmitter F2RC008A exhibits a high bias through the cycle that exceeds its upper OLM acceptance limit (Figure 3.40).

SG A STEAM FLOW transmitters F2MS001A and F2MS002A appear to drift low during the cycle, which is most likely the result of a process change throughout the cycle (Figure 3.41).

FW FLOW TO SG C transmitters F2FW008A and F2FW009A exhibit similar behavior (Figure 3.42).

Table 3.9 North Anna Unit 2 Transmitters With Potential Problems (Cycle 21)

Item	Tagname	Service	Comment
1	L2FW005A	SG B NARROW RANGE LEVEL	Deviation from average
2	L2FW007A	SG B NARROW RANGE LEVEL	Deviation from average
3	F2MS005A	SG C STEAM FLOW	Deviation from average
4	F2MS006A	SG C STEAM FLOW	Deviation from average
5	F2RC008A	RCS LOOP C FLOW	High bias

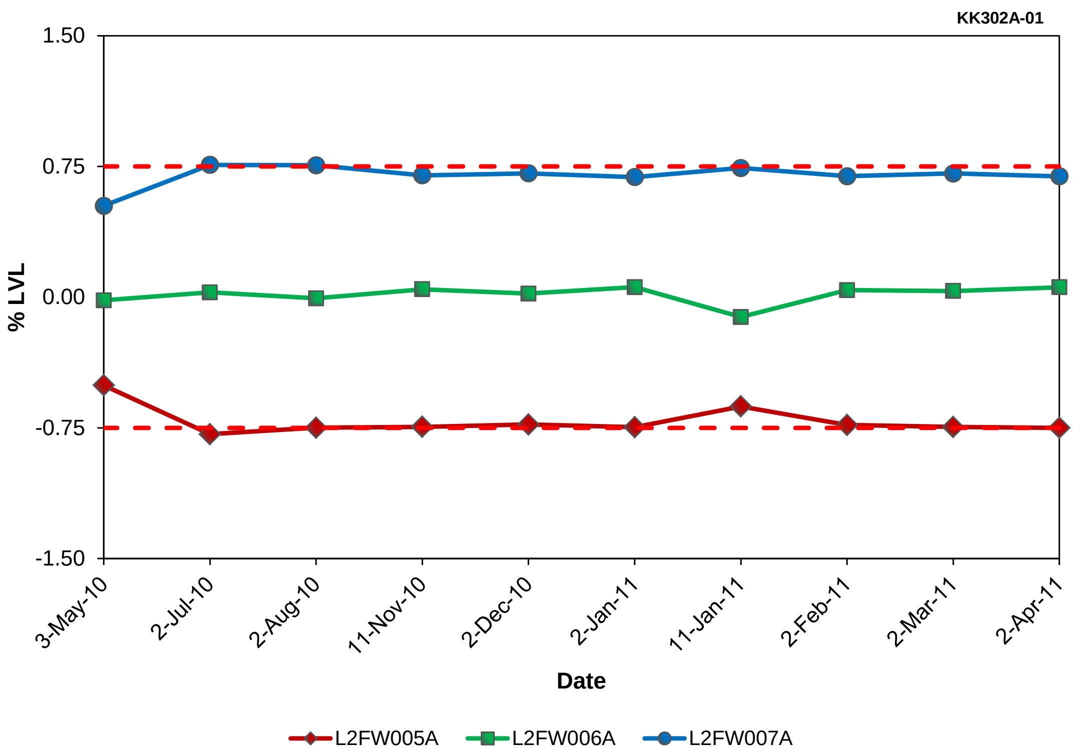


Figure 3.38 SB B LEVEL Steady-State Deviation at North Anna Unit 2 (Cycle 21)

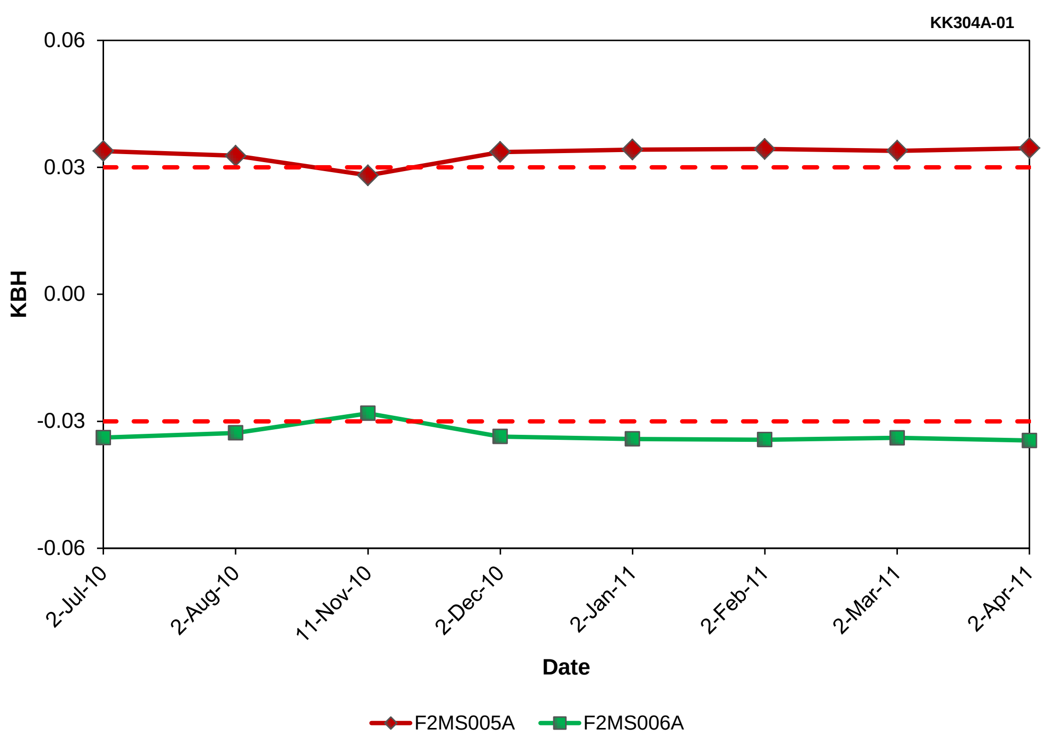


Figure 3.39 SG C STEAM FLOW Steady-State Deviation at North Anna Unit 2 (Cycle 21)

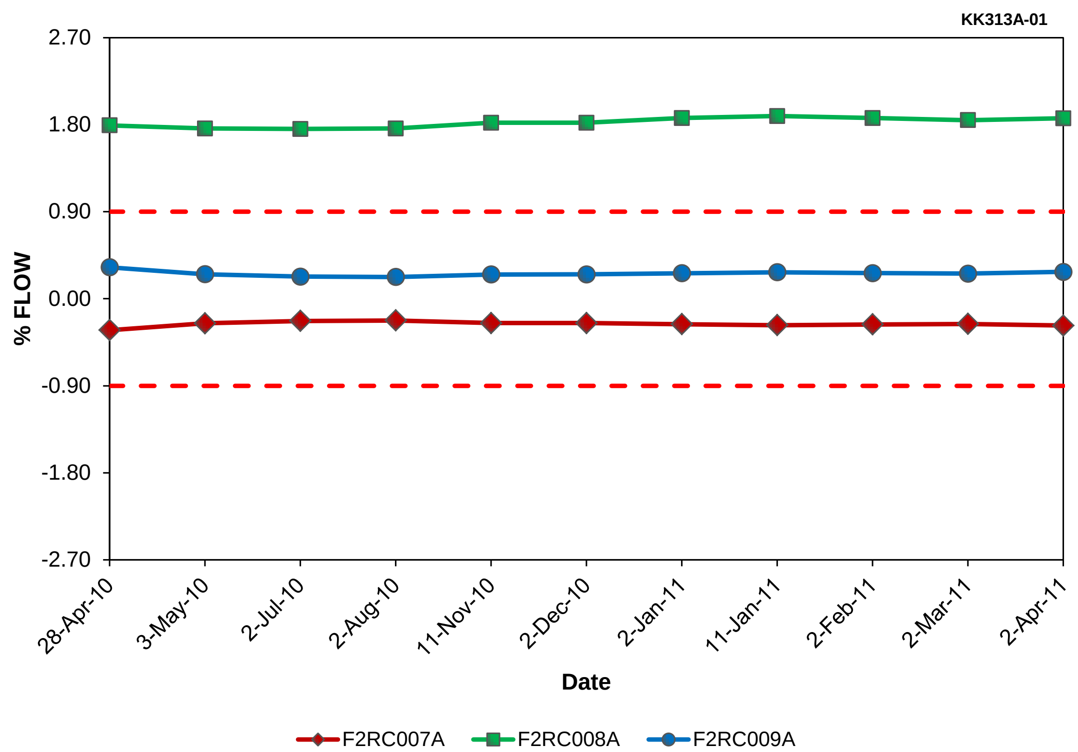


Figure 3.40 RCS LOOP C FLOW Steady-State Deviation at North Anna Unit 2 (Cycle 21)

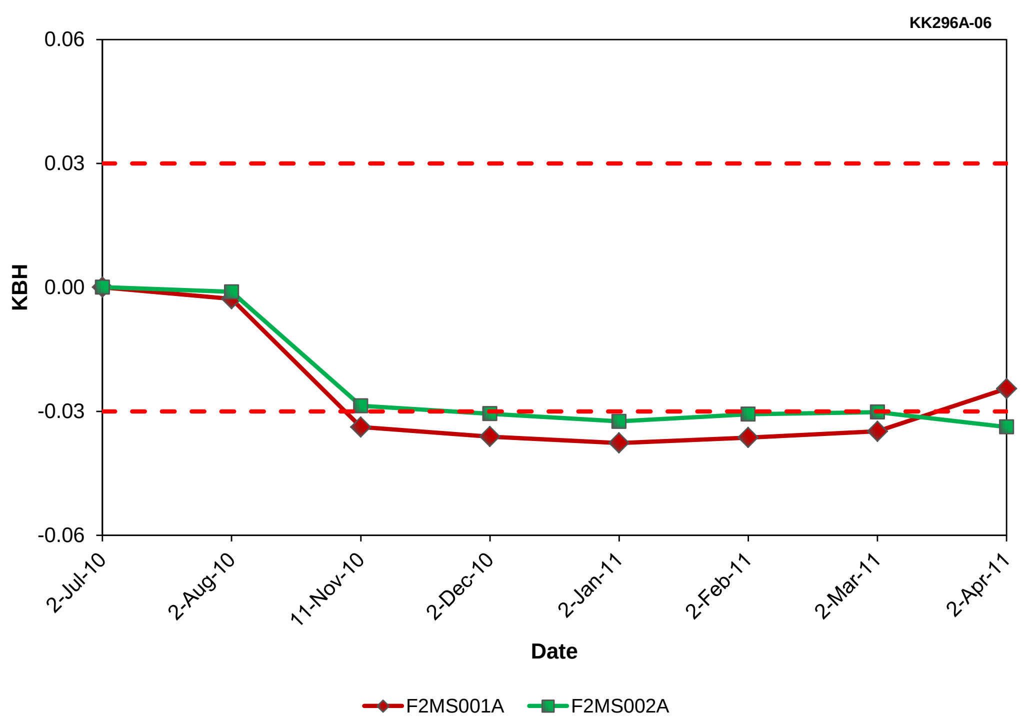


Figure 3.41 SG A STEAM FLOW Model Analysis at North Anna Unit 2 (Cycle 21)

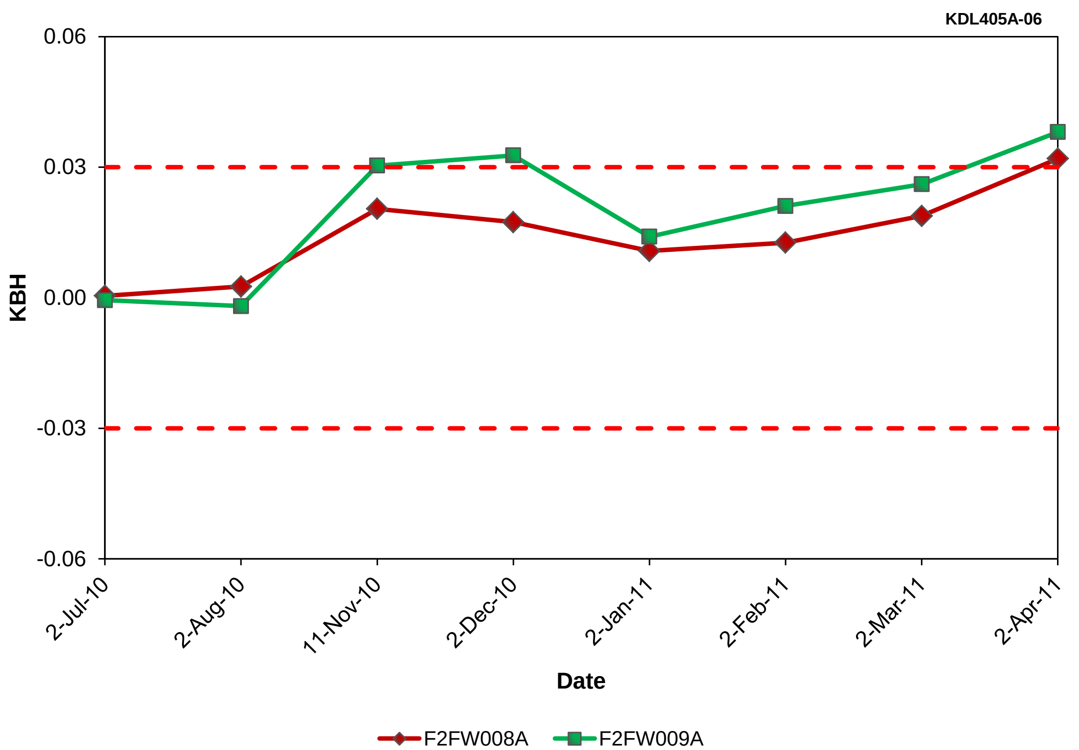


Figure 3.42 FW FLOW TO SG C Model Analysis at North Anna Unit 2 (Cycle 21)

4. LESSONS LEARNED DURING THE PROJECT

One of the most important aspects of the Phase II+ was the accumulation of experience and knowledge that came as a part of analyzing multiple cycles of data for 4 nuclear reactors. In this section, lessons learned during this project are presented that may benefit the industry or others who are planning to implement OLM in their plants.

4.1 OLM Data Acquisition

The typical path for static data acquisition is shown in Figure 4.1. Signals from the sensors of interest are terminated in instrumentation cabinets and eventually are acquired and stored by the plant computer. Downstream of the plant computer is a data historian which greatly simplifies the storage and retrieval of data (see explanation in Appendix A). However, the data compression that is often applied by data historians can be a problem for OLM algorithms, especially empirical modeling algorithms which rely on correlations between related sensors. Ideally, the plant could turn off the compression settings so that the data from the plant historian could be retrieved without compression. However, as experienced during this project, the information technology (IT) departments in charge of the historians are often reluctant to change compression settings because of limitations with data storage capacities.

At both Farley and North Anna, the compression settings of the data historians could not be turned off in order to collect sufficient data for the OLM analysis. In both cases, plant personnel involved with the project retrieved data from the plant computer itself in order to avoid problems with compression settings. However, as discovered during this project, retrieving data directly from the plant computer may not be straightforward, and is often cumbersome on plant personnel.

For the Farley plant, AMS developed a special program that periodically retrieved plant computer data that was being sent in real-time to an Excel spreadsheet. This solution worked adequately; however, when Excel was upgraded during the course of the project, it often caused the data acquisition code to stop working temporarily until the problem could be resolved. North Anna, on the other hand, was able to generate ‘log’ files from the plant computer, which provided a much easier way to obtain data than Farley.

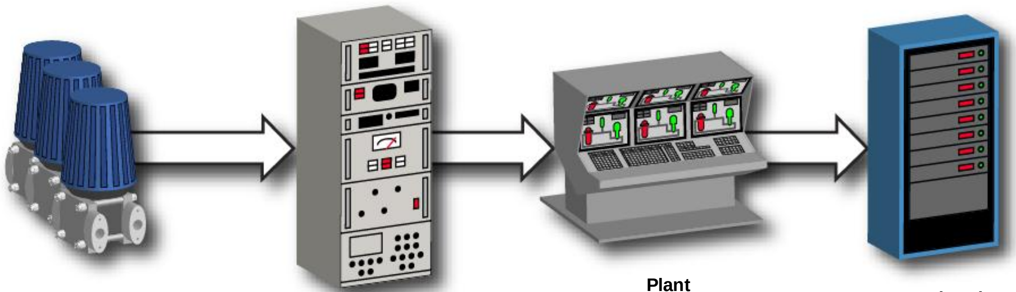


Figure 4.1: Sensor data flow to the plant computer and data historian

4.2 Analytical Modeling Experience

For the most part, the analytical models worked well throughout the project. As AMS learned over the course of the project, it is very important at the beginning of the project to meet with plant personnel when determining the model groupings. Automated tools such as cross-correlation analysis to determine model groupings are a good first step, but often relationships between diverse parameters are not necessarily linear, and thus some critical model parameters may be overlooked. Fortunately during the course of the Phase II project AMS engineers met and discussed model groupings with personnel from both Farley and North Anna and came to a consensus on what should be included in each model.

Although the models provided valuable information for most of the plant services, sometimes they would produce false alarms because of the nature of the way in which they were trained. As discussed in the Phase II report [2], the models for Farley and North Anna were trained at the start of each cycle using data from the startup and one month after startup. After much trial and error, AMS decided to include the month after startup in the model so that the monthly data would not leave the training space shortly after startup. This worked well in most cases, however, if the process being monitored changed during the cycle and exceeded the training data space, false alarms could be generated.

Figures 4.2 – 4.5 provide an example of what can happen when the process changes for a given model. Figure 4.2 shows the residual analysis of STEAM A FLOW transmitters at North Anna Unit 1 from Cycle 21. At first glance, it appears that both transmitters have drifted high during the cycle. However, closer inspection of the data reveals that what is actually happening is that the process itself is changing to a state that has not been learned by the model, which makes it appear that there is something wrong with the transmitters.

As shown in Figure 4.3, the mean value of the STEAM A FLOW transmitters correlates with the residual shown in Figure 4.2. In addition, the residual and mean of SG A FEED FLOW transmitters follows a similar increase over the same period of time. As it is unlikely that both steam flow and feed flow transmitters can both be experiencing the same exact sort of degradation, the alternative explanation for the apparent high residuals is that the process has changed. Because the models were trained with data from startup and one month after startup, if the process changes to some other state during the cycle, this could make the transmitters appear to drift.

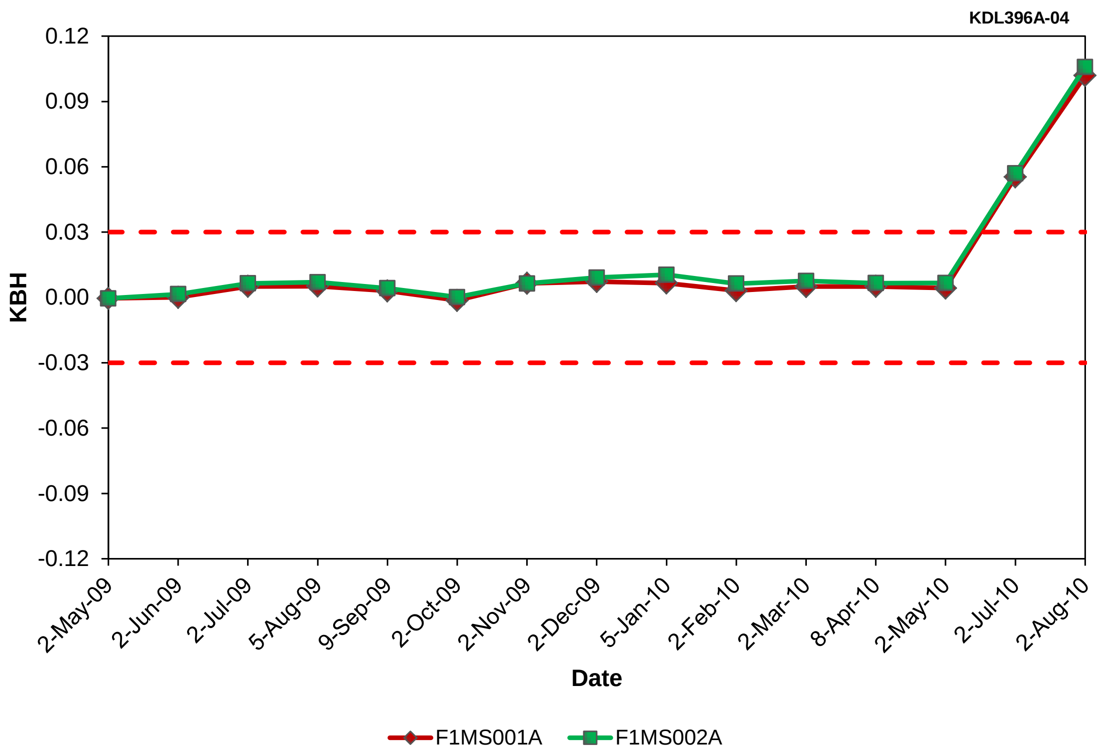


Figure 4.2 SG A STEAM FLOW Steady-State Residual at North Anna Unit 1 (Cycle 21)

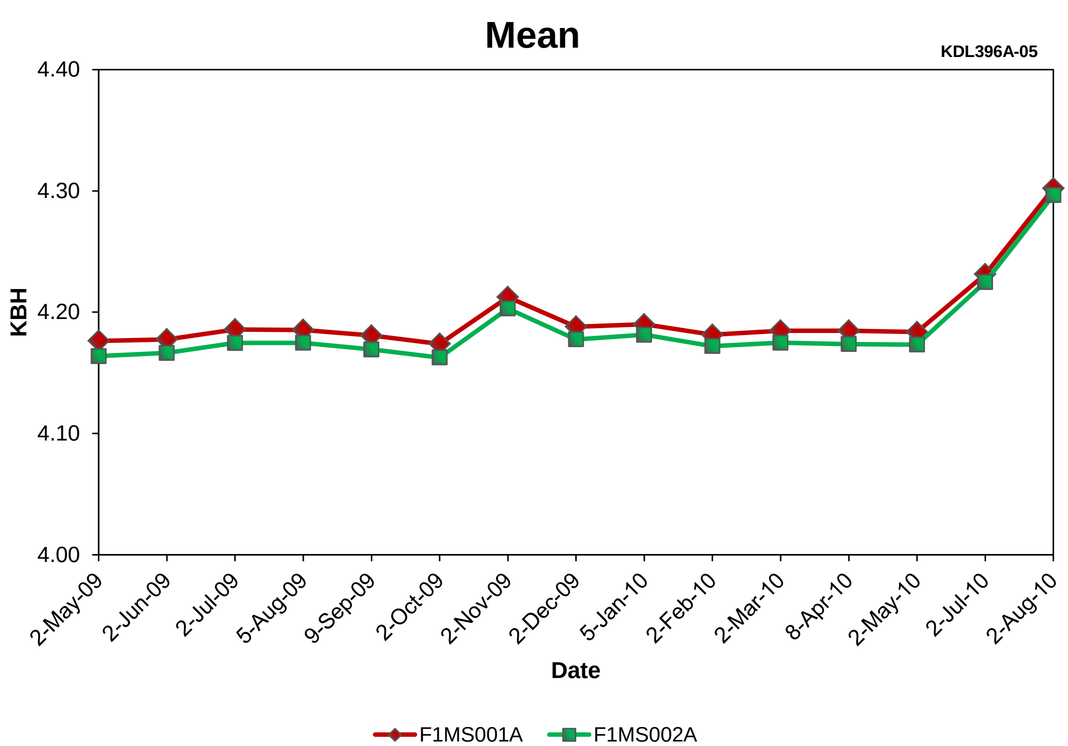


Figure 4.3 SG A STEAM FLOW Static Mean at North Anna Unit 1 (Cycle 21)

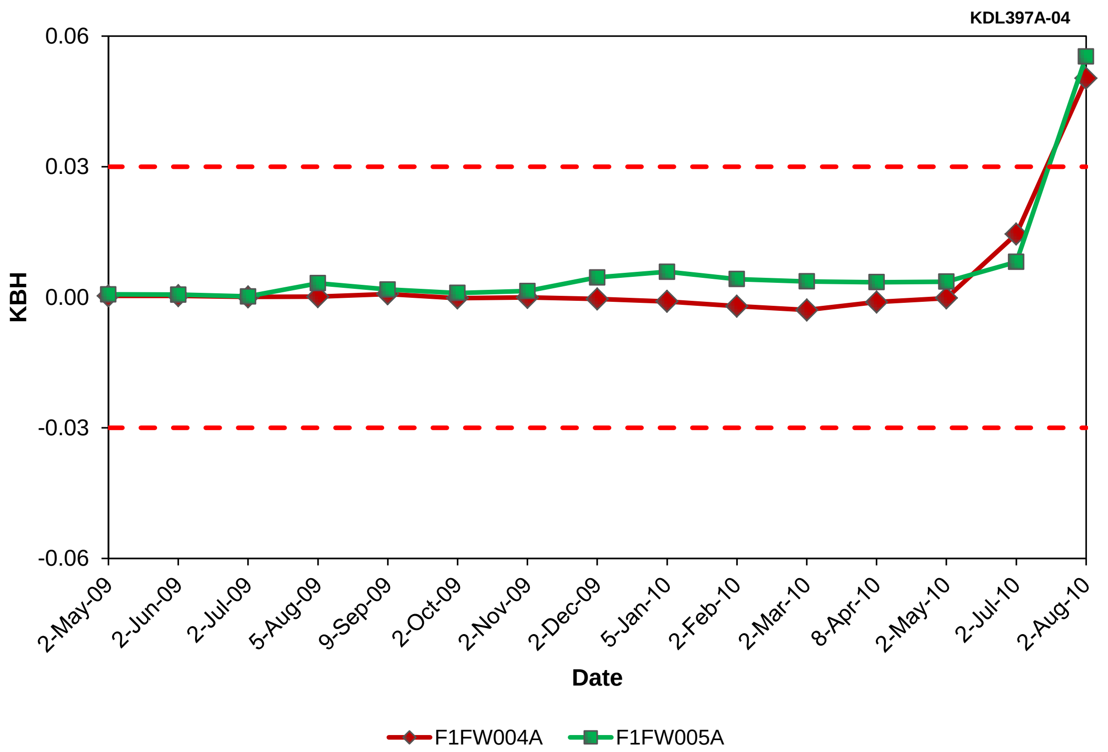


Figure 4.4 SG A FW FLOW Steady-State Residual at North Anna Unit 1 (Cycle 21)

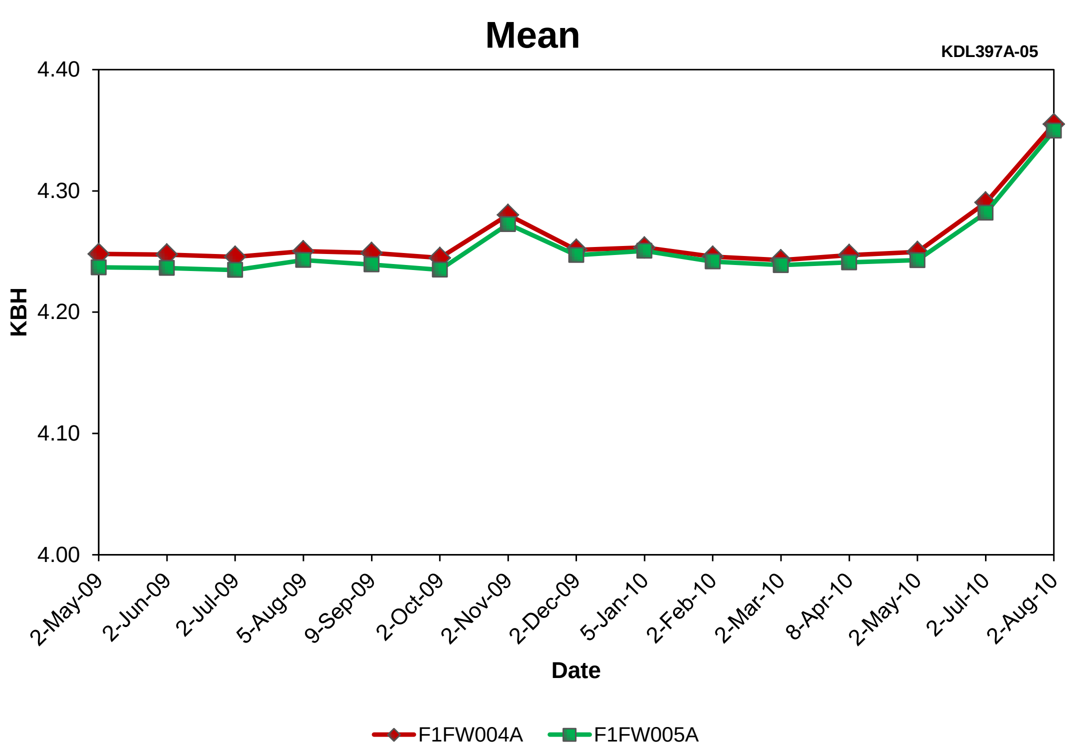


Figure 4.5 SG A FW FLOW Static Mean at North Anna Unit 1 (Cycle 21)

4.3 Differential Pressure to Flow Conversion

Flow transmitters measure a differential pressure, typically across some type of orifice plate. When these transmitters are calibrated, a differential pressure is used along with limits that are derived for the flow at operating conditions converted to differential pressure. The differential pressure data from the transmitter is converted to flow in the instrument channel on the way to the plant computer. Thus, when the flow transmitters are analyzed, the units are in terms of the flow rate.

In order to better understand the problem with this issue, consider the relationship between the mass flow rate and the volumetric flow rate (and the associated differential pressure). An equation for the mass flow rate for an incompressible fluid (with constant density) through an orifice is given by

$$\dot{m} = \rho Q = CA\sqrt{2\rho(P_1 - P_2)}$$

where

$\dot{m}$ = mass flow rate
ρ = fluid density
Q = volumetric flow rate
C = orifice flow coefficient
A = cross-sectional area of orifice hole
P_1 = upstream pressure
P_2 = downstream pressure.

To clarify the relationship, the constants are removed and the equation becomes

$$\dot{m} \propto \sqrt{(P_1 - P_2)}$$

This equation shows that the mass flow rate is proportional to the square root of the differential pressure. Therefore, when looking at the flow in terms of mass flow rate, any constant bias in the differential pressure signal will show up as the square root of that bias in the mass flow rate.

This also implies that for flows, the limits should change along the transmitter's span (due to the square root). Because the limits used for the OLM analysis are calculated at the transmitter's operating point in terms of flow, they should not be applied to other areas of the transmitter's range. However, in practice, a constant flow deviation limit is used.

Figure 4.6 provides an example of how flow signals are analyzed with constant operating point deviation limits. The figure shows the deviation of the transmitters growing exponentially toward the lower end of the range. This separation of the flow signals at the low end of the range is the result of the square root of a bias in the differential pressure of the signals. The figure also demonstrates how the theoretical limits would flare out at the low end of the range, bounding the transmitter deviations, if they were adjusted to account for the square root of the differential pressure to flow conversion.

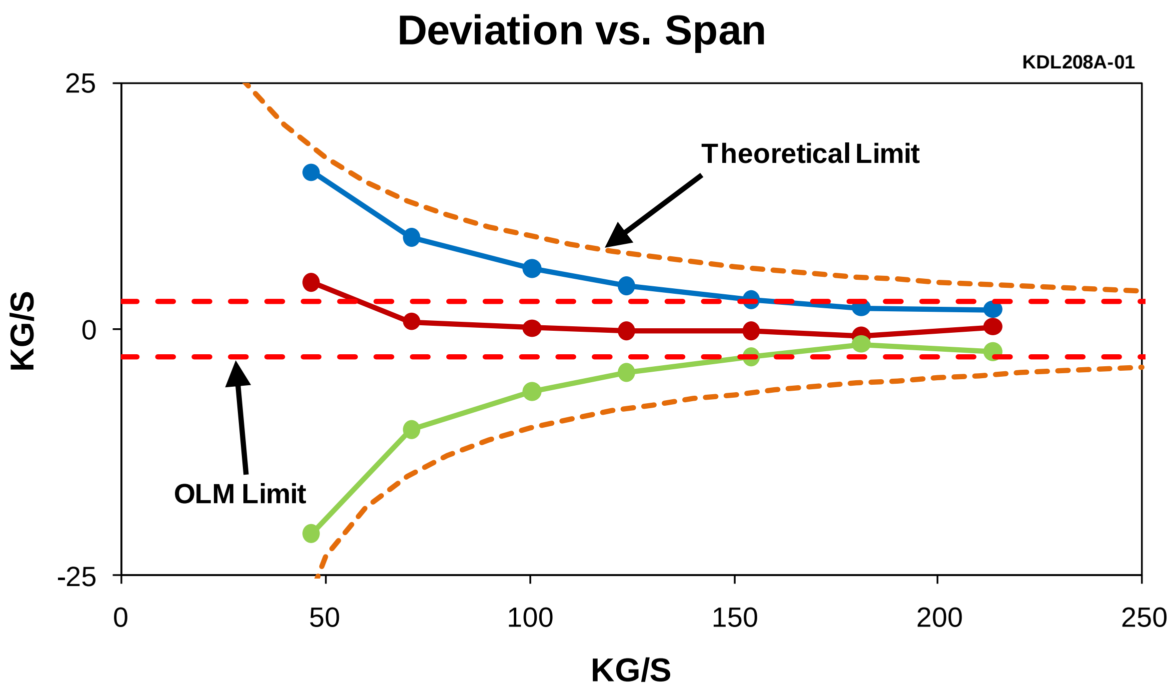


Figure 4.6 Main Steam Flow Transmitters Analyzed with OLM and Theoretical Limits

Note that the upper and lower theoretical limits are not symmetric, which adds to the complexity of the OLM analysis in terms of flow. If the flow measurements were converted back into differential pressures, they could be analyzed in terms of a constant limit, similar to manual calibrations. This would make the analysis simpler and easier for the analyst to understand at a glance.

In the analysis for Farley and North Anna, these types of deviations were considered in the final analysis and noted.

5. COMMERCIALIZATION OF OLM

As the ultimate goal of the DOE SBIR program is to develop commercial products and technologies that can be sold to existing or new customers, AMS spent considerable effort over the course of the project (using its own funds), to educate and inform potential customers of the capabilities and benefits that the OLM system can provide. These commercial activities took several forms, including meetings and conferences held at AMS headquarters, plant/corporate site visits, teleconferences, and participation in nuclear industry users groups (Table 5.1).

AMS is also marketing the products of this project on its website (www.ams-corp.com) and in other promotional materials. In particular, the OLM data acquisition system, which was developed during this project, is currently featured on the AMS website, and has been provided to the nuclear industry. For example, Sizewell B plant engineers are currently using the OLM data acquisition system to acquire I&C dynamic data on a quarterly basis, and have a commercial contract with AMS to analyze the dynamic response of the transmitters. In addition, AMS is now using the OLM system to provide the data acquisition for its normal transmitter response time service contracts for nuclear plants both in the U.S. and abroad.

In October 2010, AMS was awarded a three year Phase III grant to commercialize the OLM technology developed in Phase II and extend its applications from PWRs to BWRs.

5.1 International Exposure and Publications

The product of this project has been showcased by AMS (at its own cost) in a number of international venues to promote the use of OLM technologies in nuclear plants outside of the U.S. In addition, AMS was a key contributor to the publication of two technical documents published by the International Atomic Energy Agency (IAEA) in 2008. Referred to as 'IAEA Nuclear Energy Series' documents, the titles of these publications are 'On-line Monitoring for Improving Performance of Nuclear Power Plants Part 1: Instrument Channel Monitoring', and 'On-line Monitoring for Improving Performance of Nuclear Power Plants Part 2: Process and Component Condition Monitoring and Diagnostics' [4-5].

Table 5.1 Examples of Commercialization Activities

Date of Meeting	Customer	Meeting Type	Potential Nuclear Power Plants
March 2008	Dominion	Marketing	North Anna, Surrey
June 2008	Southern Nuclear Operating Company (SNOC)	Marketing	Farley, Vogtle, Hatch
June 2008	Rod Control Reliability Committee (RCRC)	Users Group	Nuclear Power Industry
June 2008	51st Annual ISA POWID Symposium, Scottsdale, AZ	Conference	Nuclear Power Industry
July 2008	Pressurized Water Reactor Owner's Group (PWROG)	Users Group	PWR Plants
September 2008	SNOC, Dominion, Westinghouse	Technical	Westinghouse Plants
December 2008	Luminant	Marketing	Comanche Peak
December 2008	TVA	Marketing	Sequoyah, Watts Bar, Browns Ferry
August 2009	Southern Nuclear Operating Company (SNOC)	Technical	Farley, Vogtle, Hatch
Mar. 2010	Pressurized Water Reactor Owner's Group (PWROG)	Technical	PWR Plants

In April 2009, AMS hosted a meeting for an IAEA-sponsored Coordinated Research Project (CRP) entitled 'Advanced Surveillance, Diagnostics and Prognostics (SDP) Techniques Used for Health Monitoring of Systems, Structures, and Components in Nuclear Power Plants' at AMS headquarters in Knoxville, Tennessee. The purpose of this CRP is to:

- Develop and demonstrate the use of advanced SDP techniques that can be installed and used for health monitoring of systems, structures and components in nuclear power plants
- Strengthen Member States' capabilities for optimization of nuclear power plant performance and service life by means of improved understanding of the related engineering and management areas

The results of this CRP will be a new document to be published by the IAEA when the work is completed. The meeting held at AMS involved over 50 participants from 15 countries. AMS continues to be a key contributor to this project, which is scheduled to be published in the fall of 2011.

AMS has also been heavily involved in publishing articles based on the subject of on-line monitoring during the course of this project. Table 5.2 provides a list of publications on OLM and brief descriptions of each article published by project team members.

5.2 Impact on the U.S. Nuclear Industry

One of the most significant accomplishments of this project has been the increased level of interest in OLM implementation that it has created in the U.S. nuclear industry. Those familiar with the history of OLM development in the nuclear industry will remember a similar effort headed by EPRI in the late 1990's. This effort resulted in a Safety Evaluation Report (SER) issued by the Nuclear Regulatory Commission (NRC) in July 2000 approving the use of OLM to extend the calibration intervals of nuclear plant pressure, level, and flow transmitters [6]. In fact, this SER was partly based on the results of an R&D project that AMS had performed for the NRC in the mid-1990s as documented in NUREG/CR-6343; a report that AMS wrote for the NRC [7].

Table 5.2 Publications by the Authors Related to this Project

AMS Paper Desig*	Paper Title	Author(s)	Journal/ Publication Info	Month/Year of Publication	Description of Paper
J7	Pressure Transmitter Accuracy	Hashemian, H.M. and Jiang, J.	ISA Transactions, Vol. 48, No. 4, Pages 383-388	October 2009	Key causes of calibration drift in pressure transmitters and procedures for calibrating pressure transmitters to ensure their accuracy.
J8	The State of the Art in Nuclear Power Plant Instrumentation and Control	Hashemian, H.M.	Int. J. Nuclear Energy Science and Technology, Volume 4, No. 4, pages 330-354	September 2009	Advances over the past decade in process instrumentation and control for nuclear power plants.
J10	Regulations and Standards for the Measurement of Performance and Management of Ageing of I&C Systems of Nuclear Power Plants	Hashemian, H.M.	Int. J. Nuclear Law, Volume 2, No. 4	March 2010	Regulations, standards and guidelines to formulate requirements and establish maintenance methods to verify the performance of equipment.
J11	A Practical Review of Methods for Measuring the Dynamic Characteristics of Industrial Pressure Transmitters	Hashemian, H.M., and Jiang, J.	ISA Transactions, Volume 49, Issue 1	January 2010	Methods for testing the response times of pressure transmitters in situ: power interrupt, noise analysis and pink noise techniques.
J12	Using The Noise Analysis Technique to Detect Response Time Problems in the Sensing Lines of Nuclear Plant Pressure Transmitters	Hashemian, H.M., and Jiang, J.	Progress in Nuclear Energy, ISSN 0149-1970, Volume 52, Issue 4, pp. 367-373	May 2010	Only the noise analysis technique provides an effective means for testing response times when a nuclear plant is operating.
J13	Implementing Online Monitoring in Nuclear Power Plants	Hashemian, H.M	IEEE Transactions on Nuclear Science	May 2010	On-line monitoring techniques make it possible to automate and analyze the evaluation of instrument accuracy and reliability while a plant is operating.
J15	Integrated Online Condition Monitoring System for Nuclear Power Plants	Hashemian, H.M.	Kerntechnik, Volume 75, No. 5, pp. 231-242	September 2010	Online monitoring uses data acquired while a nuclear power plant is operating to continuously assess the health of the plants sensors, processes, and equipment.

*Paper designation corresponds to AMS' list of publications

AMS Paper Desig*	Paper Title	Author(s)	Journal/ Publication Info	Month/Year of Publication	Description of Paper
J16	Applying Online Monitoring for Nuclear Power Plant Instrumentation and Control	Hashemian, H.M.	IEEE Transactions on Nuclear Science, Volume 57, Number 5, Part III	October 2010	A practical review of the state-of-the-art means for applying OLM data acquisition in nuclear power plant instrumentation and control, qualifying or validating the OLM data, and then analyzing it for static and dynamic performance monitoring applications.
J19	Aging Management of Instrumentation & Control Sensors in Nuclear Power Plants	Hashemian, H.M.	Nuclear Engineering and Design, Volume 240, Issue 11, pages 3781-3790.	November 2010	A review of aging management methods, their effectiveness, and their interrelation provides a foundation for understanding the next stage in the evolution of online monitoring.
J20	On-Line Monitoring Applications in Nuclear Power Plants	Hashemian, H.M.	Progress in Nuclear Energy 53, Issue 2, 167-181	March 2011	Online monitoring technologies with particular emphasis on detecting sensing line blockages, testing the response time of pressure transmitters, monitoring the calibration of pressure transmitters online, cross calibrating temperature sensors in situ, assessing equipment condition, performing predictive maintenance of reactor internals, monitoring fluid flow, and extending the life of neutron detectors.
J23	Ensuring Plant Safety & Reliability	Hashemian, H.M.	Nuclear Plant Journal, Volume 29, No. 2, pages 38-40	March/April 2011	A question and answer session regarding online condition monitoring systems.
M21	Instrumentation and Control in Nuclear Power Plants	Hashemian, Hash	**SciTopics**. Retrieved May 25, 2010, from http://www.scitopics.com/Instrumentation_and_Control_in_Nuclear_Power_Plants.html	May 2010	Nuclear power plant instrumentation and control consists of hardware that controls and ensures the safety of NPPs by acquiring data from sensors monitoring the status of process variables such as temperature, pressure, and level; conditions and isolates these sensor signals; displays and processes the sensor data on records, indicators, and the plant computer; and issues commands to controllers, safety logic circuitry, or safety actuation systems.

*Paper designation corresponds to AMS' list of publications

AMS Paper Desig*	Paper Title	Author(s)	Journal/ Publication Info	Month/Year of Publication	Description of Paper
M22	Listening in Real Time	Hashemian, H.M.	Nuclear Engineering International Magazine, pp. 13-20	April 2010	Online monitoring technologies and methods to anticipate, identify, and resolve equipment and process problems to ensure plant safety and efficiency.
M26	Predictive Maintenance Techniques	Hashemian, Hash	**SciTopics**. Retrieved June 14, 2010, from http://www.scitopics.com/Predictive_Maintenance_ Techniques.html	June 2010	Despite advances in predictive maintenance technologies, time-based and hands-on equipment maintenance is still the norm in many industrial processes.
M27	The Noise Analysis Technique for Testing Pressure Sensor Response Time	Hashemian, Hash	**SciTopics**. Retrieved June 14, 2010, from http://www.scitopics.com/The_Noise_Analysis_Technique_for_Testing_Pressure_Sensor_Response_Time.html	June 2010	The noise analysis technique is normally used for in-situ response time testing of pressure, level, and flow transmitters.
M30	Process Sensors for Nuclear Power Plants	Hashemian, H.M.	*SciTopics.* Retrieved September 23, 2010, from http://www.scitopics.com/Process_Sensors_for_Nuclear_Power_Plants.html	July 2010	The latest advances in sensors and transmitters for the nuclear power industry in the next ten years are fiber-optic and wireless sensors.
M31	Data Acquisition for Nuclear Power Plant Instrumentation and Control	Hashemian, H.M.	*SciTopics*. Retrieved September 23, 2010, from http://www.scitopics.com/Data_Acquisition_for_Nuclear_Power_Plant_Instrumentation_and_Control.html	July 2010	Online monitoring techniques make it possible to automate and analyze the evaluation of instrument accuracy and reliability while a nuclear plant is operating.
M34	Data Qualification for Online Monitoring of Nuclear Power Plant Instrumentation and Control	Hashemian, H.M.	*SciTopics*. Retrieved September 23, 2010 from http://www.scitopics.com/Data_Qualification_for_Online_Monitoring_of _Nuclear_Power_Plant_Instrumentation_and_Control.html	July 2010	After data for online monitoring of nuclear power plant instrumentation and control has been acquired it must be qualified for use by OLM algorithms.
B7	Nuclear Plant Instrumentation and Control System Performance Monitoring	Hashemian, H.M.	<u>Instrument Engineers' Handbook: Process Software and Digital Networks</u>, Volume 3, Edition 4/Chapter 61	August 2011	OLM technologies and new diagnostic and prognostic methods to anticipate, identify, and resolve equipment and process problems and ensure plant safety, efficiency, and immunity to accidents.

*Paper designation corresponds to AMS' list of publications

AMS Paper Desig*	Paper Title	Author(s)	Journal/ Publication Info	Month/Year of Publication	Description of Paper
I37	On-Line Monitoring and Calibration Techniques in Nuclear Power Plants	Hashemian, H.M.	Presented at the International Conference on Opportunities and Challenges for Water Cooled Reactors in the 21st Century, International Atomic Energy Agency (IAEA), Vienna, Austria	October 2009	OLM and on-line calibration of critical process monitoring sensors such as RTDs, thermocouples, and pressure transmitters.
N114	Assessing the Dynamic Performance of Sensors in Nuclear Power Plants Using Low Frequency Plant Computer Data	Morton, G.W., Hashemian, H.M., Shumaker, B.D., Wunderlich, R.J.	Presented at the 6th American Nuclear Society (ANS) International Topical Meeting on Nuclear Plant Instrumentation, Controls, and Human Machine Interface Technologies (NPIC&HMIT), Knoxville, TN, USA	April 2009	Progress of a DOE R&D effort to use OLM to assess the accuracy and reliability of instrumentation and health of nuclear power plants.
N119	On-Line Maintenance of Nuclear Plant I&C Systems for Operation Beyond 40 and 60 Years	Hashemian, H.M.	Transactions of 2009 Annual Meeting of American Nuclear Society, Atlanta, GA	June 2009	A listing of predictive maintenance techniques for management of aging of process instrumentation and control systems such as sensors, cables, connectors, process-to-sensor interfaces, and other plant equipment.
N123	On-Line Monitoring Techniques for Improved Reliability and Maintenance of I&C Systems in Research Reactors	Hashemian, H.M. and O'Hagan, R.	Presented at the ANS NPIC&HMIT, held concurrently with the ANS National Meeting, Las Vegas, NV, USA	November 2010	On-line monitoring techniques which can be used to streamline and improve the maintenance practices in research reactors.
N124	An Integrated System for Static and Dynamic On-Line Monitoring of Nuclear Power Plant Systems and Components	Hashemian, H.M., Shumaker, B.D., Wunderlich, R.J., Caylor, S.D., and Morton, G.W.	Presented at the ANS NPIC&HMIT held concurrently with the ANS National Meeting, Las Vegas, NV, USA	November 2010	Nuclear power plants (NPPs) are instrumented with numerous sensors that can be monitored while the plant is on-line to verify the accuracy and reliability of the sensors themselves, and as importantly, for plant diagnostics, aging management, and health monitoring.

*Paper designation corresponds to AMS' list of publications

Although the NRC issued a SER in the year 2000 in favor of OLM, the industry activity slowed down as no utility wanted to be the first to implement OLM because of the unproven benefits and the uncharted approach to technical specification amendments that are needed. However, with the success of the Phase II project, interest in OLM technologies has risen again as evidenced by the support of the participating utilities in this project and the activities recently initiated by the Pressurized Water Reactor Owners Group (PWROG).

In October 2009, the PWROG initiated a multi-year project intended to pursue generic licensing of OLM methods to reduce the I&C maintenance burden associated with transmitter calibrations in Westinghouse, Babcock & Wilcox (B&W), and Combustion Engineering (C-E) PWR designs. Initially, the PWROG planned to approach the generic licensing issue in accordance with the recommendations set forth in [6]. In 2006, the V.C. Summer plant prepared a submittal to modify their technical specifications to extend transmitter calibrations following the NRC approach; however, the effort was ultimately withdrawn from submittal, leaving the U.S. nuclear industry with no successful path to follow for getting transmitter calibration extension approved.

The approach to transmitter calibration extension set out in the SER places the burden of the safety case on the particular OLM software algorithms employed by the plants to determine the calibration status of their transmitters. Although the SER does not specifically recommend any particular OLM algorithm, each plant is required to submit with their technical specification change detailed information about their OLM algorithms, including how the OLM algorithms are not sensitive to common-mode drift and how process estimate uncertainties produced by the OLM algorithms are calculated. In fact, one of the primary reasons the V.C. Summer technical specification change was not reviewed by the NRC was because it lacked specific information about the OLM algorithms that were to be used.

The Sizewell B plant in the United Kingdom, which is the only plant to date that has received approval for transmitter calibration extension from their regulatory authority, took a different approach. In Sizewell's approach, the burden of the safety case is centered around historical evidence from their maintenance records showing that their transmitters do not systematically drift, rather than relying solely on OLM algorithms to determine the calibration status of their transmitters. In Sizewell B's approach, OLM algorithms are used as a performance monitoring tool to provide more frequent monitoring of transmitter performance than the traditional manual calibration method, which only assess transmitter performance every eighteen months. Approaching their technical specification change in this way helped Sizewell B to avoid having to provide detailed explanations of their OLM algorithms, and also gave them the flexibility to not be tied to one particular OLM algorithm.

In March 2010, the PWROG invited representatives from AMS, Westinghouse, the Electric Power Research Institute (EPRI), Sizewell B, and the University of Tennessee (UT) to discuss how to best approach generic licensing of OLM for transmitter calibration extension. At the conclusion of the meeting, the PWROG decided to change the project scope to follow Sizewell B's approach of basing their safety case on historical transmitter drift and using OLM as a performance monitoring tool. This approach adopted by the PWROG will follow the methodology found in industry documents NEI 04-10 Rev 1 [8] and TSTF-425 [9] which provide NRC-approved guidance for utilities to set up their own programs for surveillance frequencies. The new PWROG project scope includes the following technical tasks:

1. Determine the impact of transmitter calibration extension on probabilistic risk analysis (PRA), defense-in-depth, and safety margins.
2. Performing a generic transmitter drift study using statistical analysis of transmitter maintenance records.
3. Developing guidance to determine OLM acceptance criteria.

Funding for the new project scope was authorized by PWROG management in October 2010, and the project is expected to be completed in November 2012. The PWROG requested that AMS perform the generic transmitter drift study. As the drift study work falls outside of the scope of the Phase II+ project, AMS will perform this work under a commercial contract with the PWROG.

6. CONCLUSIONS AND FUTURE WORK

The OLM system designed and developed during this project has been demonstrated on data from four operating nuclear reactors as part of an SBIR research project conducted by AMS under the supervision of the DOE. As described in this report, the OLM system integrates static and dynamic OLM techniques to provide an objective assessment of the health and condition of a nuclear power plant and its equipment, and the reliability and accuracy of its instrumentation. The OLM results obtained over the course of this report indicate that the majority of nuclear power plant transmitters do not exhibit drift over typical 18-month fuel cycles. In fact, out of the 507 individual transmitters analyzed during this report, which covered a period including 9 fuel cycles, only 7% (35 transmitters) exhibited anomalous behavior during the cycle. This is an encouraging result in that it shows that OLM can be used to demonstrate that transmitters do not lose their calibrations over fuel cycles, and also that OLM can give operators a tool to detect instrumentation problems as they occur.

Throughout the course of the project, NPPs in the U.S. and abroad actively participated by providing plant computer data, engineering resources, and plant access to test the implementation of the OLM system. In the U.S., interest generated in OLM technologies as a result of this project provided the impetus for the formation and authorization of a project to be carried out by the PWR Owner's Group (PWROG). This PWROG project, which began in 2010, is aimed at providing NRC-approved guidance for utilities to set up their own surveillance frequency programs which will be used to extend transmitter calibration intervals. The project is expected to be completed in two years. As the scope of this project includes Westinghouse, B&W, and C-E PWRs, it could potentially impact 69 out of the 104 NPPs currently operating in the U.S. AMS has been invited by the PWROG to participate in this project by performing a generic transmitter drift study using statistical analysis of transmitter maintenance records.

In October 2010, AMS was awarded a Phase III SBIR from the DOE to commercialize OLM technologies researched and developed over the course of this project and to extend it to Boiling Water Reactor (BWR) applications. This project is planned to be completed in September 2013, and will result in commercial OLM tools and applications that will be used to provide enhanced OLM capabilities for both PWRs and BWRs in the U.S. and worldwide.

7. REFERENCES

1. *Phase I Final Report – On-Line Monitoring of Accuracy and Reliability of Instrumentation and Health of Nuclear Power Plants*. Hashemian, H.M., AMS Corporation, June 2007.

2. *Final Project Report – On-Line Monitoring of Accuracy and Reliability of Instrumentation and Health of Nuclear Power Plants*. Hashemian, H.M., AMS Corporation, February 2010.

3. *Implementation of On-Line Monitoring to Extend the Calibration Interval of Pressure Transmitters in Nuclear Power Plants*. EPRI, Palo Alto, CA: 2009. 1019188.

4. *On-line Monitoring for Improving Performance of Nuclear Power Plants Part 1: Instrument Channel Monitoring*. International Atomic Energy Agency (IAEA), IAEA Nuclear Energy Series No. NP-T-1.1, Vienna, Austria: 2008. http://www-pub.iaea.org

5. *On-line Monitoring for Improving Performance of Nuclear Power Plants Part 2: Process and Component Condition Monitoring and Diagnostics*. International Atomic Energy Agency (IAEA), IAEA Nuclear Energy Series No. NP-T-1.2, Vienna, Austria: 2008. http://www-pub.iaea.org

6. *On-Line Monitoring of Instrument Channel Performance TR-104965-R1 NRC SER,* EPRI, Palo Alto, CA: 2000. 1000604.

7. *On-Line Testing of Calibration of Process Instrumentation Channels in Nuclear Power Plants*. Hashemian, H.M., U.S. Nuclear Regulatory Commission, NUREG/CR-6343. Washington, D.C.: 1995.

8. *Risk-Informed Technical Specifications Initiative 5b, Risk-Informed Method for Control of Surveillance Frequencies*, Nuclear Energy Institute, NEI 04-10 Rev. 1, Washington, D.C.: 2007. http://www.nrc.gov (ADAMS accession number ML071360456)

9. *Transmittal of TSTF-425, Revision 3, Relocate Surveillance Frequencies to Licensee Control - RITSTF Initiative 5b, Sections 3.1.1 - 3.7.5*, EXCEL Services Corporation, Rockville, Maryland: 2009. http://www.nrc.gov (ADAMS accession number ML090850627.

APPENDIX A

On-Line Monitoring Implementation in Nuclear Power Plants

<u>AMS White Paper</u>

On-Line Monitoring Implementation in Nuclear Power Plants

B.D. Shumaker, G.M. Morton, and H.M. Hashemian

December 2008

On-line monitoring (OLM) implementation in nuclear power plants involve data acquisition, data qualification, and data analysis. These aspects each depend on whether the data is used for static condition monitoring applications (e.g. instrument calibration monitoring) or dynamic condition monitoring applications (e.g. sensor response time testing, core barrel vibration measurements). This paper covers each of the three aspects of the OLM implementation separately.

1. OLM Data Acquisition

There are several possibilities for obtaining OLM data. These are:

- Retrieve the data manually
- Retrieve the data that is already available in the plant computer
- Install a new means to automatically acquire the data
- Use a combination of these options

These requirements depend on whether OLM is being used for static performance monitoring or dynamic performance monitoring applications. These applications are discussed in this paper together with their corresponding data acquisition requirements.

1.1 Data acquisition for static performance monitoring

Static OLM techniques are primarily concerned with recognizing slow moving changes in sensors or plant processes due to drift, sensor degradation, or gradual equipment failure. For applications such as equipment performance monitoring, a sample rate of at least 1 sample/minute is sufficient for static analysis. However, for applications such as calibration monitoring or cross-calibration where startup or shutdown transients will be used, faster rates in the order of 1 to 10 seconds are required.

1.1.1 Manual data acquisition

Manual data collection process involves connecting a multimeter to test points in the instrumentation cabinets, and manually recording the sensor readings (Figure 1).

There are a few advantages to acquiring OLM data manually. For example, the measurements are often simple, and plant personnel are often trained and familiar with taking voltage measurements from test points. Also, most plants have a number of voltage measurement equipment already, so the cost of equipment is minimal. However, there are several drawbacks that can often make the manual method impractical for many static OLM techniques, especially those techniques that involve comparing several sensors at one time. These drawbacks are:

- Limited measurement capability
- Significant time required to take measurements
- Increased probability of making errors when recording measurements
- Increased trip risk while sensors are in test

1.1.2 Data from plant computer

Nuclear power plants are often equipped with the means to collect and store the output of process sensors. The data can be retrieved either directly from the plant computer or through the plant data historian. Figure 2 shows a simplified data flow from the sensors to the plant computer. Most plants also employ a separate data historian to archive data from the plant computer. The historian obtains data from the plant computer and provides additional storage and other capabilities.

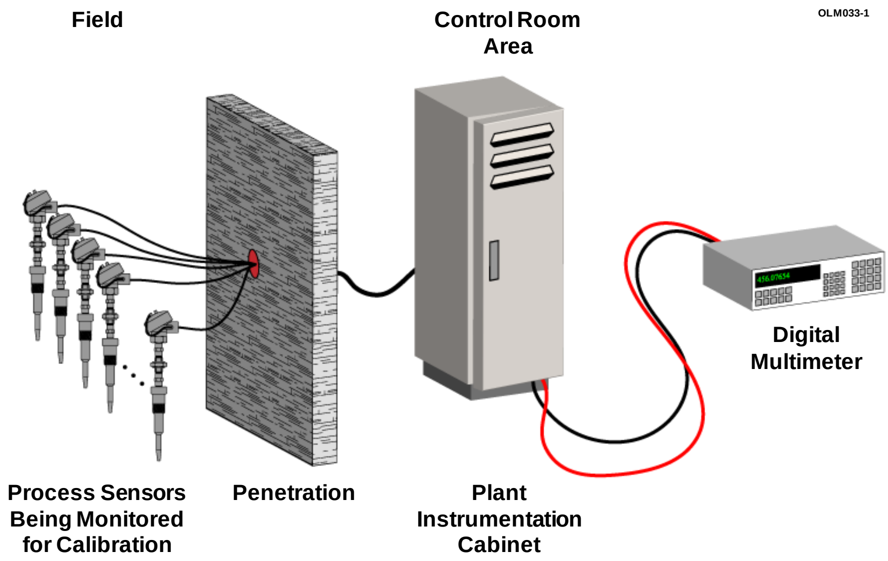


Figure 1: Manual acquisition of OLM data for RTD cross-calibration

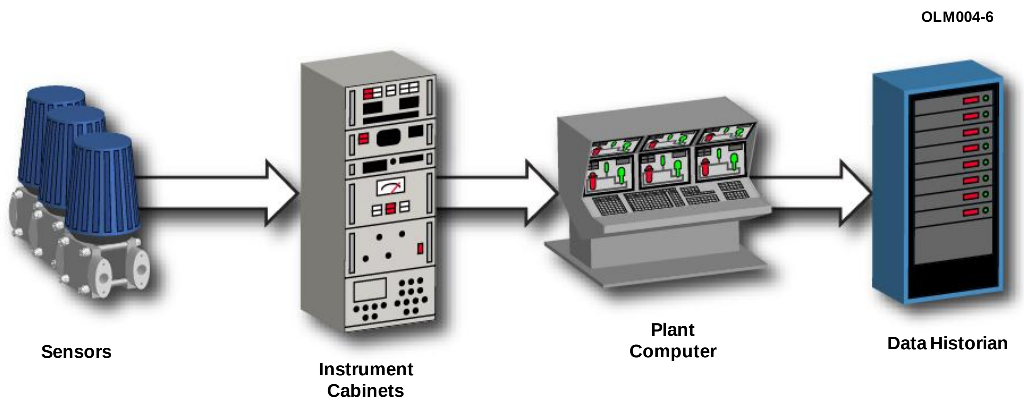


Figure 2: Sensor data flow to the plant computer and data historian

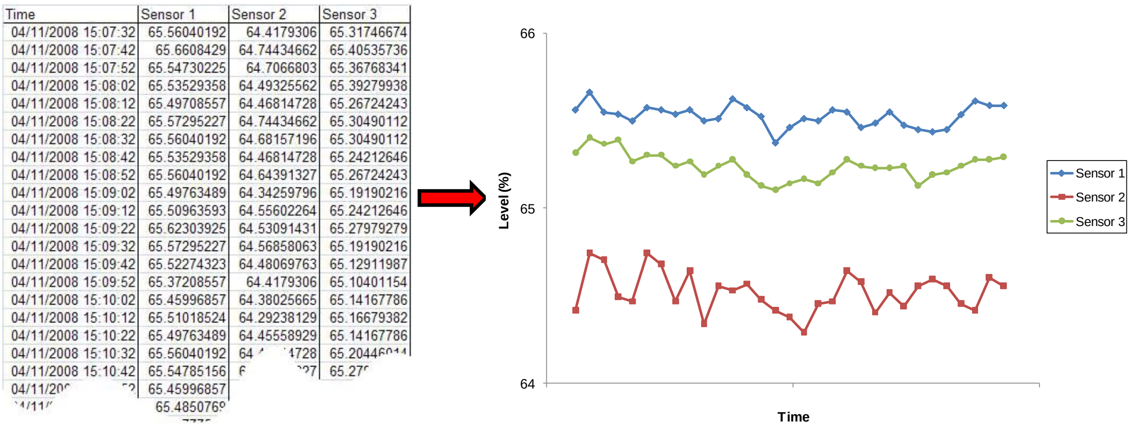
Typically, the measured sensor values are converted to engineering units before they are stored in the plant computer to facilitate easy understanding by plant personnel. In addition to the measured values, each data point is time-stamped when the data is acquired. Figure 3 shows a typical set of data from the plant computer, along with the timestamps for the measurement.

Although the plant computer provides a means for engineers to view plant process data, there are often limitations associated with typical nuclear plant computers that make OLM difficult or reduce the capabilities of OLM for equipment and process condition and health monitoring. The main limitations of typical plant computers for OLM are:

- **Storage** – Typical plant computers in service in the nuclear industry are often limited in their ability to store data. This stems from the fact that plant computers were initially installed for live process monitoring and not for long-term trending and/or modeling. Most plant computers provide ways to log real-time data for later analysis, however, as many OLM techniques require days or even weeks of data, the process of collecting the data can become cumbersome for plant personnel.

- **Software Interface – Software access to the plant computer is often** restricted to proprietary interfaces written by the plant computer manufacturer. This makes it more difficult for plant personnel or third-party developers to write customized retrieval programs or to format the plant data for analysis by another vendor.

Limitations with the plant computer such as those listed above have prompted most nuclear power plants to incorporate data historians to provide expanded capabilities to their plant computer systems. Data historians provide several potential advantages over basic plant computers that address the limitations listed above, and allow the plant computer data to be used for a variety of applications at nuclear power plants. These advantages include:



Time	Sensor 1	Sensor 2	Sensor 3
04/11/2008 15:07:32	65.56040192	64.4179306	65.31746674
04/11/2008 15:07:42	65.6608429	64.74434662	65.40535736
04/11/2008 15:07:52	65.54730225	64.7066803	65.36768341
04/11/2008 15:08:02	65.53529358	64.49325562	65.39279938
04/11/2008 15:08:12	65.49708557	64.46814728	65.26724243
04/11/2008 15:08:22	65.57295227	64.74434662	65.30490112
04/11/2008 15:08:32	65.56040192	64.68157196	65.30490112
04/11/2008 15:08:42	65.53529358	64.46814728	65.24212646
04/11/2008 15:08:52	65.56040192	64.64391327	65.26724243
04/11/2008 15:09:02	65.49763489	64.34259796	65.19190216
04/11/2008 15:09:12	65.50963593	64.55602264	65.24212646
04/11/2008 15:09:22	65.62303925	64.53091431	65.27979279
04/11/2008 15:09:32	65.57295227	64.56858063	65.19190216
04/11/2008 15:09:42	65.52274323	64.48069763	65.12911987
04/11/2008 15:09:52	65.37208557	64.4179306	65.10401154
04/11/2008 15:10:02	65.45996857	64.38025665	65.14167786
04/11/2008 15:10:12	65.51018524	64.29238129	65.16679382
04/11/2008 15:10:22	65.49763489	64.45558929	65.14167786
04/11/2008 15:10:32	65.56040192	[illegible]	[illegible]
04/11/2008 15:10:42	65.54785156	[illegible]	[illegible]
[illegible]	65.45996857		
[illegible]	[illegible]		

Figure 3: Typical data from the plant computer

- **Increased Storage Capacity** – Data historians typically employ 'compression' algorithms that only store data when a signal has changed by some user-defined amount, or if a maximum time has elapsed. Historians also employ interpolation algorithms that estimate the value of a given sensor if an actual physical measurement does not exist in the historian for a requested time. This compression/interpolation scheme greatly reduces the number of measurements that are physically stored, and thus longer periods of data can be stored and retrieved from the historian than with the plant computer alone.

- **Software Interface** – Many plant historian manufactures provide standard software interfaces such as ActiveX, Open DataBase Connectivity (ODBC), or Object Linking and Embedding for Process Control (OPC) to access the archived data. These standard interfaces make it easier for plant personnel to write their own customized retrieval programs without having to learn the plant computer manufacturer's proprietary interface. For example, a historian that incorporates an ActiveX interface could access the plant data archive with a familiar program such as Microsoft Excel.

Data historians have made accessing archived plant computer data relatively easy for plant personnel, and as a result, plant engineers are often familiar with the process of retrieving data from the plant computer for analysis. For many applications, such as trending sensor values over long periods of time, or comparing snapshots of sensor values, the data from the historian is sufficient. However, features of data historians such as compression present some challenges to applications such as OLM that must be addressed for OLM to work properly.

1.1.3 <u>Custom data acquisition</u>

An alternative to acquiring data manually or from the plant computer for static analysis is to provide a dedicated data acquisition system. Figure 4 shows the

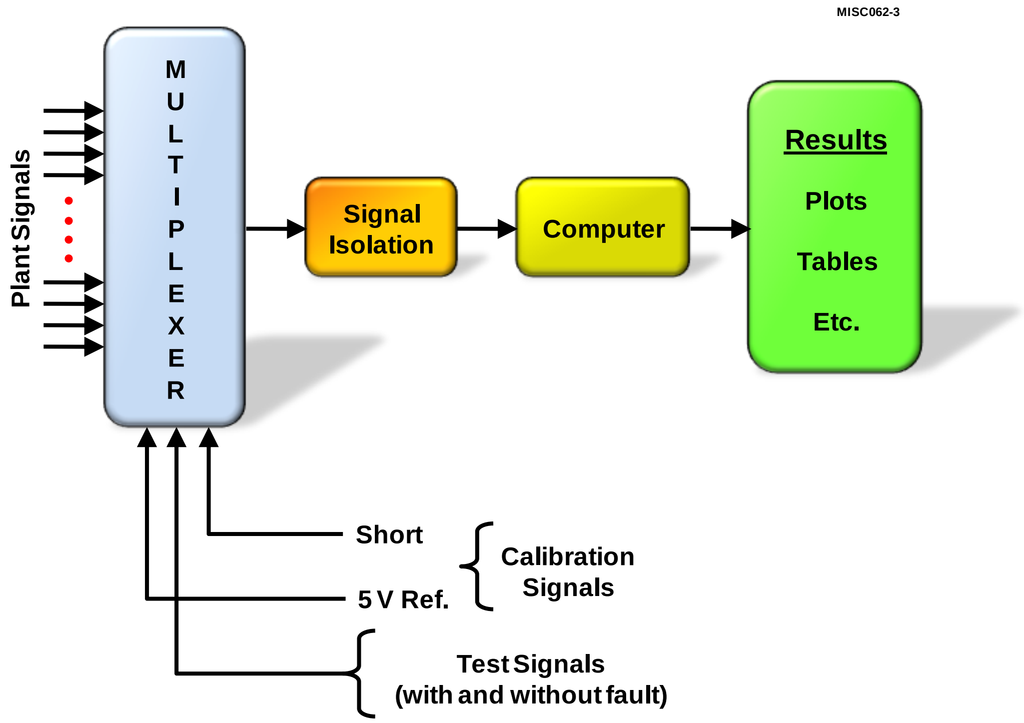


Figure 4: Custom data acquisition system

components of a dedicated data acquisition system for on-line calibration monitoring, including input test signals to verify the calibration and proper operation of the data acquisition system itself. Custom OLM data acquisition systems should be designed to sample data from numerous instruments and store the data for subsequent analysis.

1.2 Data acquisition for dynamic performance monitoring

Dynamic data analysis typically requires data sampled at higher frequencies than available in the plant computer data (i.e., 1 Hz to 1 kHz). For this reason, a dedicated data acquisition system is needed to acquire the data. In addition to acquiring the data at a high frequency, the dedicated data acquisition system also provides a means to remove the static component of a signal and amplify the fluctuations, which allows for more accurate dynamic analysis.

Figure 5 shows how one may begin with the raw signal, which includes both the static and the dynamic components, and then extract the noise from that signal. The first step in this process is to remove the static component. This is accomplished by adding a negative bias to the sensor output or by using a high-pass electronic filter. Next, the signal is amplified and passed through a low-pass filter. The low-pass filter removes the extraneous noise and provides anti-aliasing before sending the signal through an analog-to-digital (A/D) converter to a data acquisition computer. The data acquisition computer samples the data with an appropriate sampling rate and stores it for subsequent analysis.

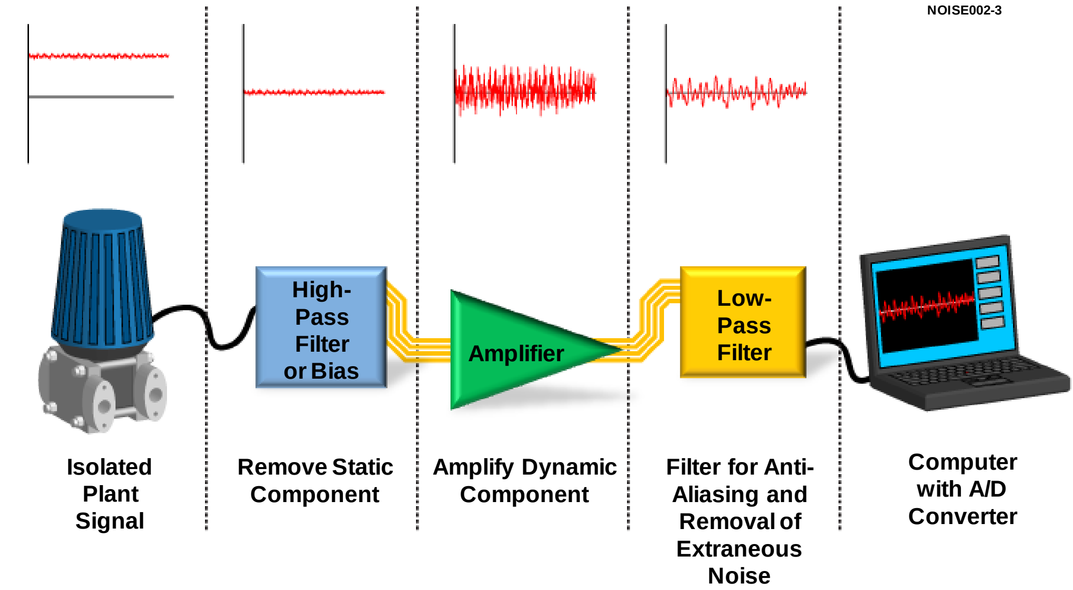


Figure 5: Block diagram of the noise data acquisition sequence

2. OLM Data Qualification

Once the OLM data has been acquired, either from the plant computer or by a dedicated data acquisition system, it must be evaluated and qualified for use by OLM algorithms. This chapter describes how OLM data is qualified.

2.1 Static data qualification

Experience has shown that data from the plant computer or data historian is not always ready for OLM analysis immediately after it is acquired. There are several common problems with data from the plant computer that must be addressed before OLM analysis can begin. In fact, in developing programs for OLM techniques, one of the most difficult challenges is preparing the data for analysis. This section describes some of the problems with the data that is retrieved from a plant computer.

2.1.1 Compressed data

The primary purpose of compressing data is to reduce the hardware resources required for storing the data. Rather than expending resources storing the same data values over and over, historians typically record data only if it has changed significantly from the previously stored value, or if a maximum time between stored data samples has elapsed. This method greatly reduces the required amount of stored data points. Figure 6 shows an example of compressed data from a nuclear power plant and the interpolated data compared to the original un-compressed data. As the figure shows, the higher frequency signals are typically lost by the data compression. This results in a loss of correlation between various compressed signals which could reduce the effectiveness of some static OLM techniques such as empirical modeling [EPRI, 2004]. For this reason, it is best to reduce or turn off the data compression when collecting data for OLM.

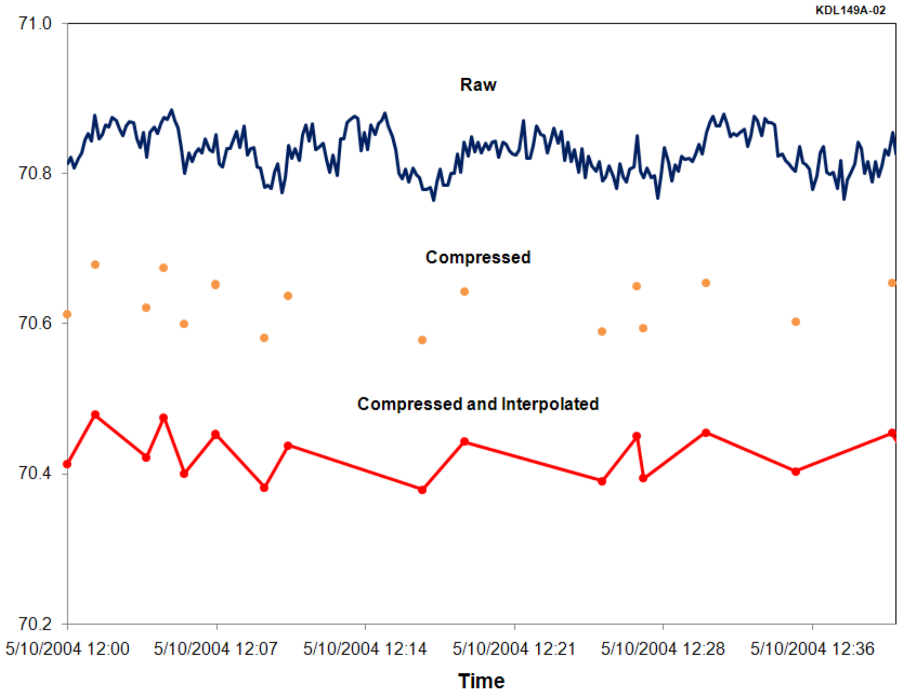


Figure 6: Compressed data from a nuclear plant data historian

2.1.2 Missing data

Often there are gaps in the plant computer data from one or more sensors. This 'missing data' can occur for various reasons including errors in data acquisition or plant maintenance in the sensor channel. An example of missing data is shown in Figure 7.

2.1.3 Outliers and spikes

Another common problem with plant computer data is the presence of spikes and outliers in the data. These spikes are commonly caused by channel checks or calibrations that are performed on the instrumentation when the data was retrieved. Figure 8 shows an example of data from a channel calibration check.

These types of problems may be difficult for software programs to automatically remove as the spikes due to channel checks or calibrations typically remain within the calibrated range of the sensor. In these cases, manual removal of the bad data values may be required.

2.1.4 Stuck data

Another common problem that is frequently encountered with plant computer data is the presence of 'dead' spots in the data where the value of given sensor or sensors

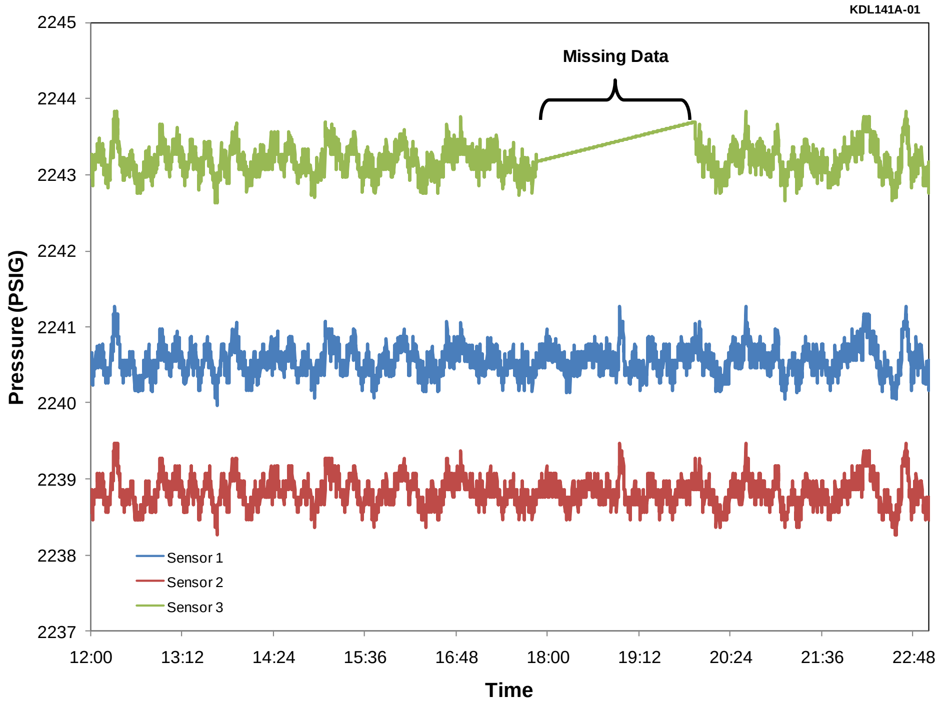


Figure 7: Missing data record in measurements from a nuclear power plant

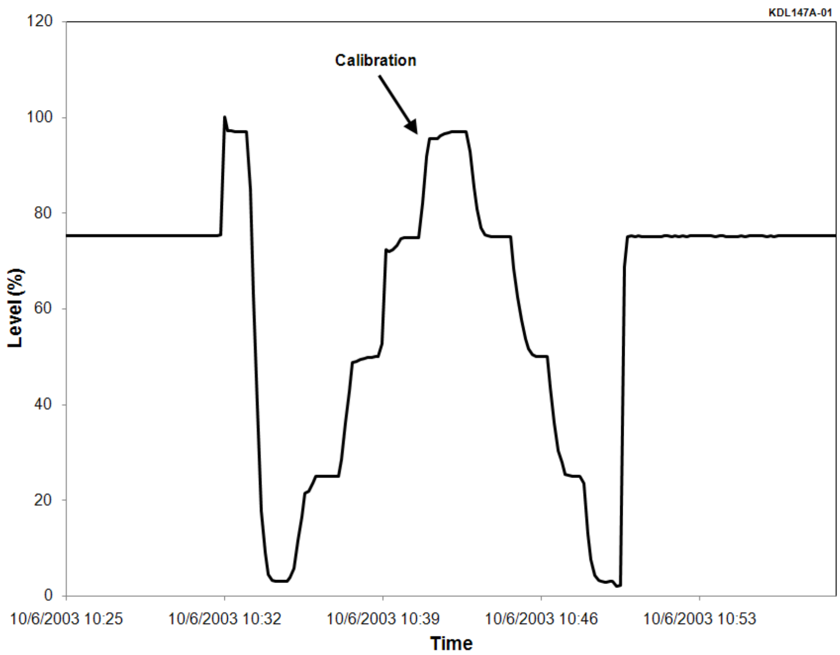


Figure 8: OLM data from a nuclear power plant computer sampled while the instrumentation channel was under calibration

remains fixed at a value for an unusually long period of time. Figure 9 shows an example of a sensor whose values are stuck, while other redundant sensors measuring the same process are shown to fluctuate as expected. These types of problems are also difficult to detect automatically because the sensor values are often within their normal operating range. More sophisticated data cleaning programs must be written to catch anomalies such as these.

2.2 Dynamic analysis data qualification

Prior to any dynamic OLM analysis, the suitability of the data must be examined by scanning and screening the raw data to ensure a reliable analysis. Because data for dynamic analysis is not normally taken from the plant computer, the common data problems associated with plant computer data do not apply. However, it is still important to evaluate and qualify dynamic data before analyzing it. Often, qualification of dynamic OLM data is accomplished by examining various statistical properties of the data such as:

- APD Plot – a visualization of a signal’s distribution
- Variance – a measure of signal amplitude
- Skewness – index of signal asymmetry
- Kurtosis – index of the ‘flatness’ of a signal’s distribution

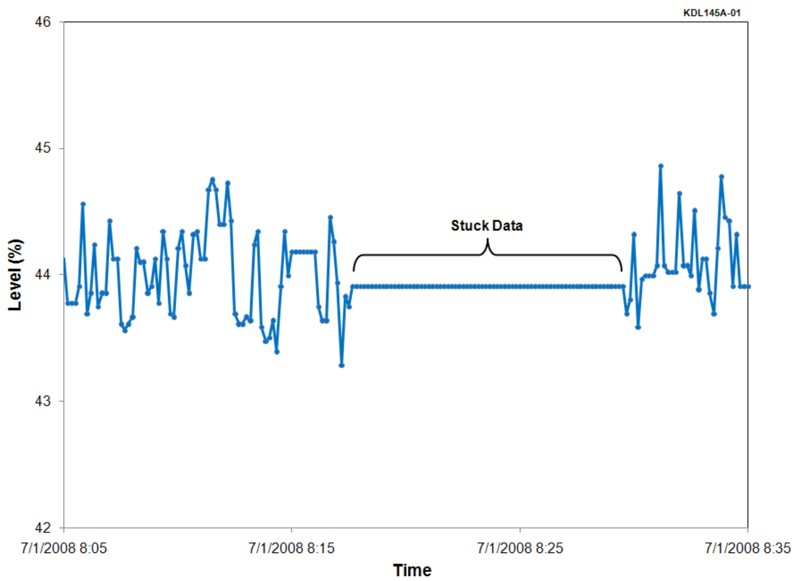


Figure 9: Illustration of 'stuck' data (data from a PWR plant computer)

Almost all nuclear plant noise signals from properly operating sensors and systems should have Gaussian distributions. As such, the distributions of signals are examined before any rigorous dynamic OLM analysis begins. This is accomplished by using data qualification algorithms that check for the stationarity and linearity of the data. This includes plotting the APD of the data for visual inspection of skewness and nonlinearity as well as calculating the skewness, flatness, or other descriptors of noise data to ensure that the data has a normal distribution and does not contain any undesirable characteristics. Trending these descriptors is also a way of evaluating changes in the process sensors which may warrant investigation.

Figure 10 shows two APDs for a normal and a defective sensor in a nuclear power plant. Note that the APD of the defective sensor deviates significantly from a Gaussian (Normal) distribution. In further examination, this sensor was found to have degraded and had become very nonlinear.

A signal's similarity to a Gaussian distribution can also be determined by calculating the skewness of the signal. Skewness is an index of the symmetry of the signal or the behavior of the signal above and below the mean value. The skewness is computed as:

$$Skewness = \frac{1}{N} \sum_{i=1}^{N} \frac{\left(x_i - \overline{x}\right)^3}{\sigma^3} \tag{1}$$

Data which is symmetrical above and below its average value will have a skewness value of zero. Figure 11 illustrates the APDs of a normal and a defective sensor.

There are higher moments of the noise data such as kurtosis that is given by:

$$Kurtosis = \frac{1}{N} \sum_{i=1}^{N} \frac{\left(x_i - \overline{x}\right)^4}{\sigma^4} \tag{2}$$

Kurtosis is a measure of the peakedness or flatness of a distribution. Figure 12 illustrates the notion of kurtosis. The peakier APD has a higher kurtosis than the flatter APD. The kurtosis value for a Gaussian signal is normally equal to 3.0. Often in data qualification algorithms, the kurtosis is divided by 3.0, so that Gaussian signals have a kurtosis of 1.0.

The concept of kurtosis and its values are better understood by examining the distributions shown in Figure 12. The top example shows a distribution with the majority of the signal in the tails and uniformly distributed in the middle, giving a low kurtosis. The bottom example shows a distribution with a long tail that yields a high kurtosis. The middle example shows a Gaussian distribution with a kurtosis of 1.0. As the kurtosis departs from 1.0, the distribution departs from a Gaussian distribution.

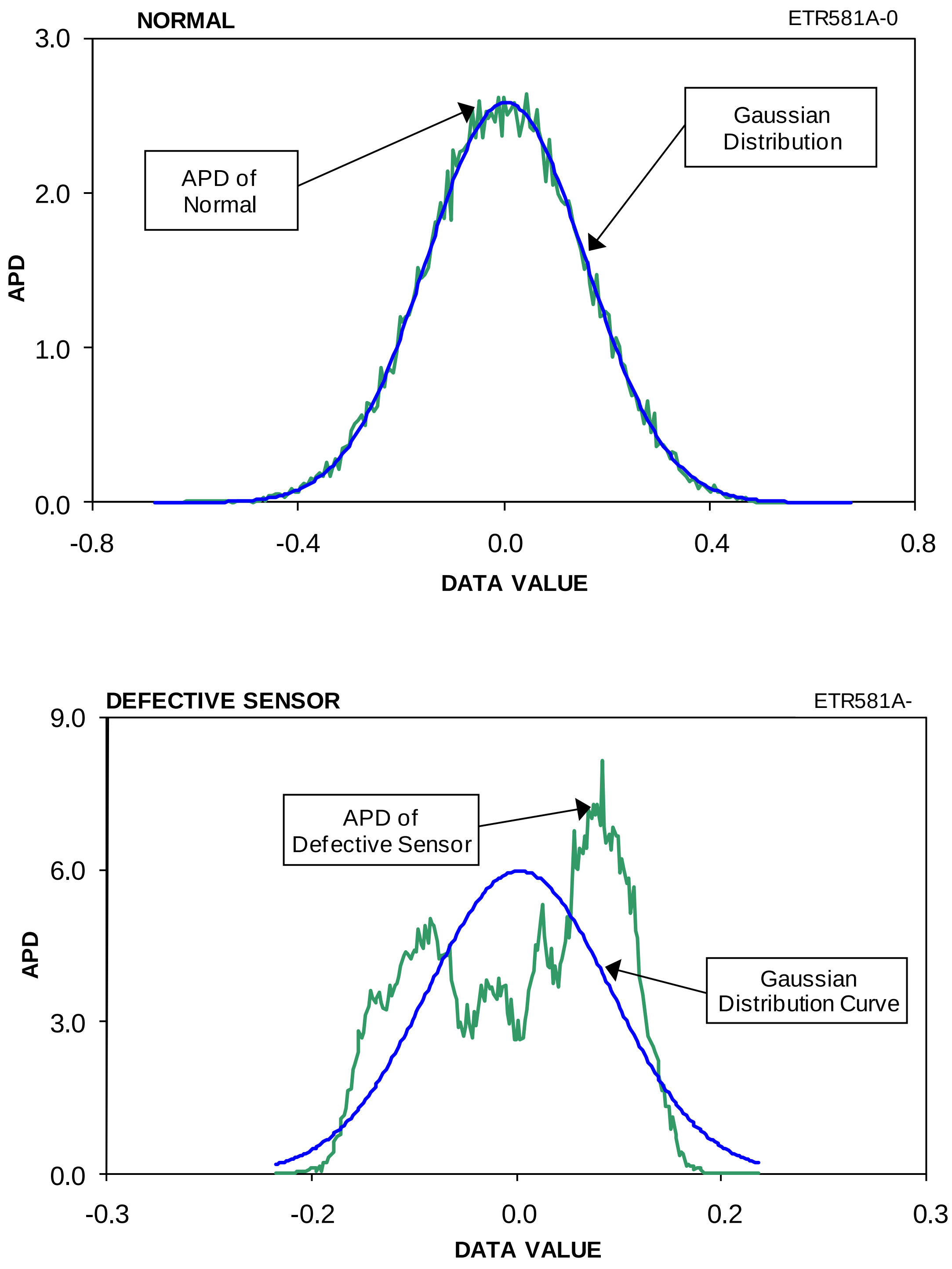


Figure 10: APDs of a normal and a defective sensor

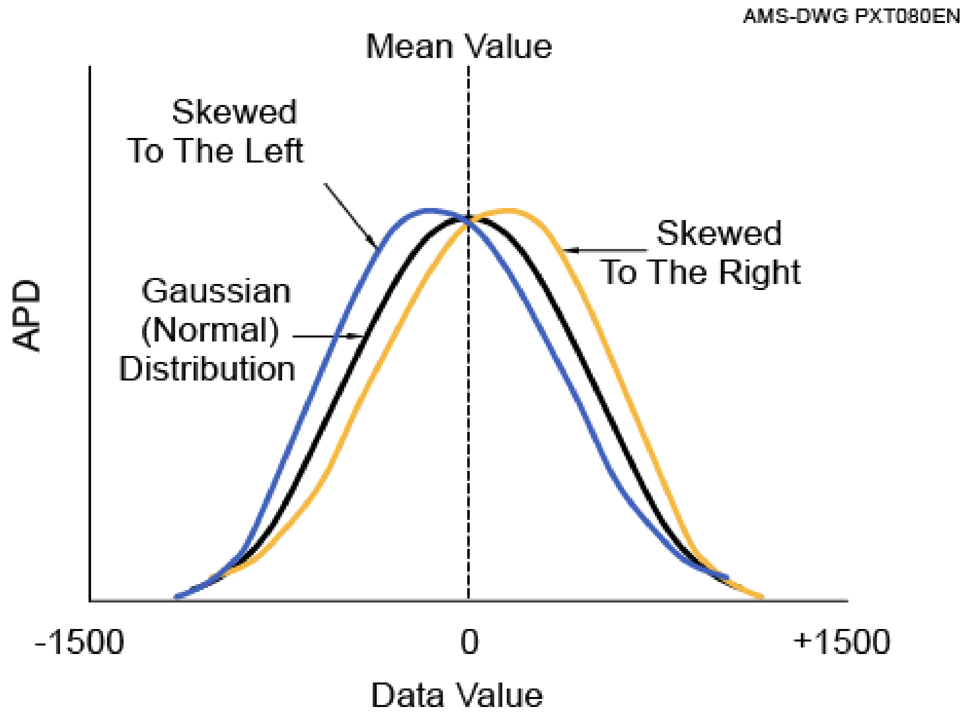


Figure 11: Illustration of noise signal asymmetry in terms of skewness

3. OLM Data Analysis

An important aspect of OLM implementation in a nuclear power plant is the choice of algorithms for analysis of static and dynamic data. This chapter explains the types of algorithms that are available, and some of the advantages and disadvantages of using these algorithms.

3.1 Static OLM analysis

The main objective of static OLM analysis is to detect out-of-normal situations in sensors or equipment that indicate a sensor is drifting out of tolerance, or that equipment is behaving abnormally. Most techniques involve using an algorithm to determine a process estimate and then subtracting the measured sensor values from the process estimate to form a deviation or residual. The deviations or residuals of each individual sensor are then checked for abnormal values by various fault detection methods.

3.1.1 Data analysis by trending

Perhaps the simplest way of analyzing static data is to trend simple statistical quantities such as the mean and standard deviation.

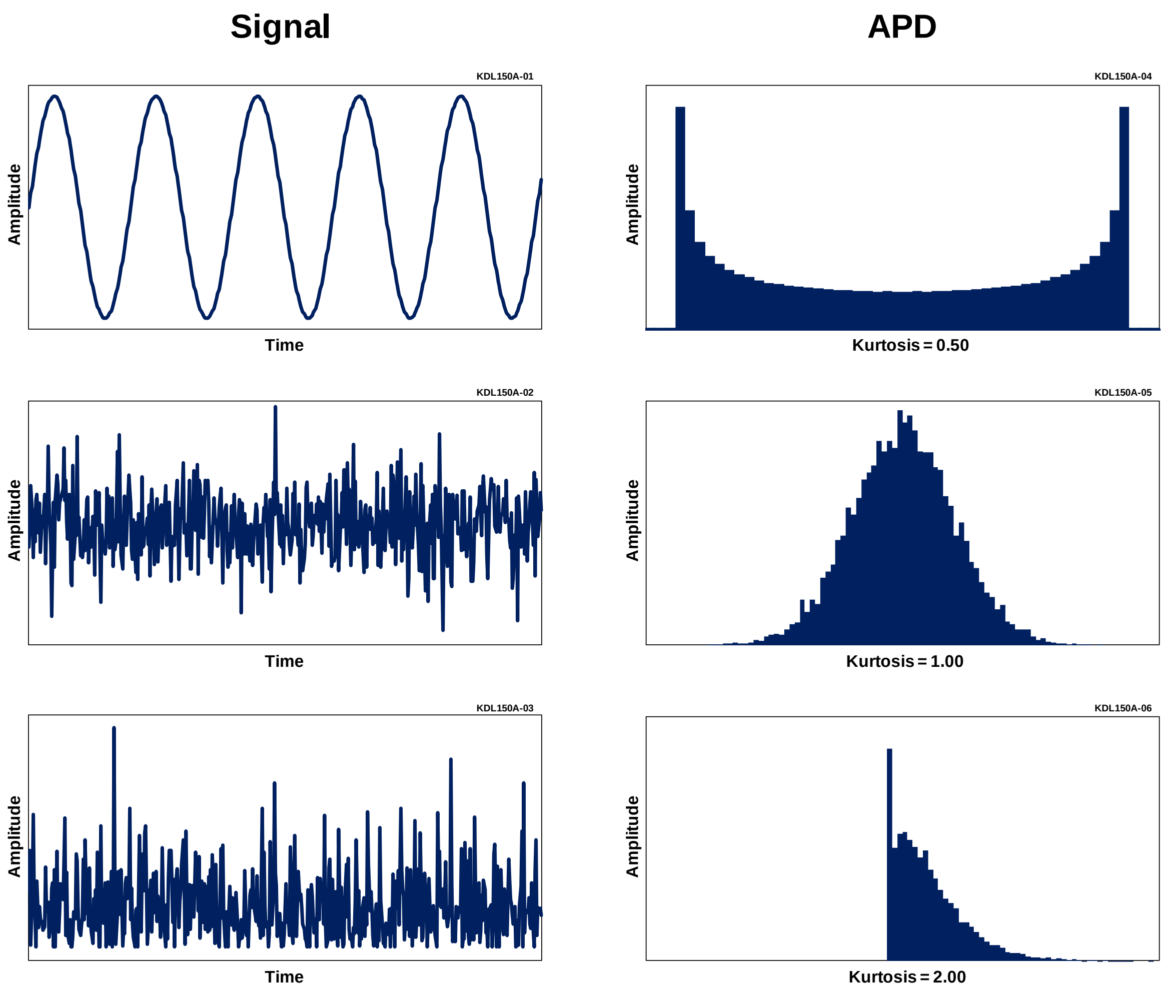


Figure 12: Distribution of signals with various kurtosis values

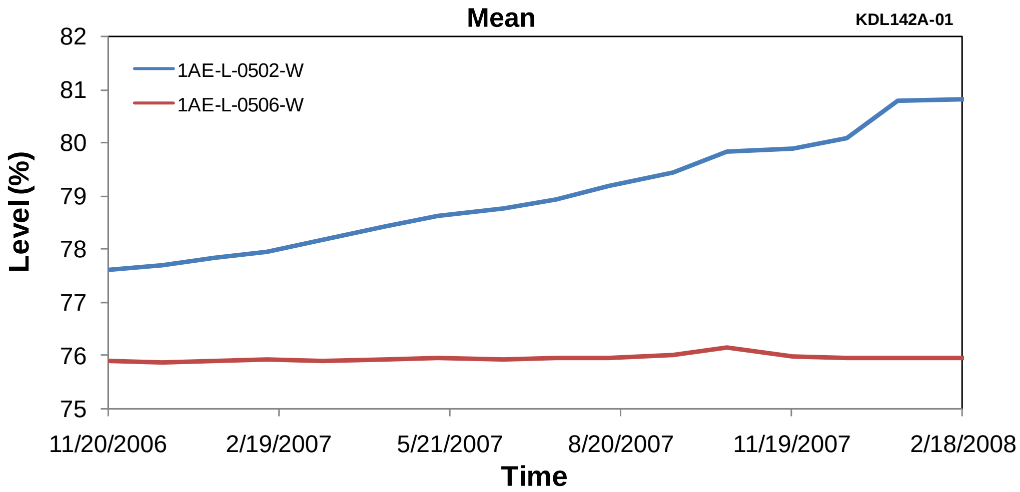
Figure 13 shows plots of the mean and standard deviation of two steam generator (SG) level transmitters over one fuel cycle. It is clear from just looking at the means that one of the transmitters is drifting upwards while one is remaining constant. This example shows that just monitoring some basic statistical parameters can identify if there is a change in the performance of the signal. Once a change is identified, it must be determined if the process is changing or the sensor is changing. As in Figure 13, the casual observer will assume that the plant process is stable thus indicating the change in the signal is due to the sensor drifting. However, it is possible that the plant process is actually drifting up and the second sensor output that appears constant is actually drifting down masking the plant drift. When sufficiently redundant sensors are not available for a process parameter, diverse signals may be used to determine if the plant process parameter is constant. In any event, the simple statistical calculations can detect changes in the data. The bottom standard deviation plot in Figure 13 shows that there is no change in the standard deviation of the signal, indicating that there are no gross dynamic problems with this process parameter and associated sensors.

3.1.2 Redundant sensor averaging

Most nuclear plant safety process parameters are instrumented with redundant sensors. The most straightforward technique for determining drift or abnormality in nuclear plant data is comparison of redundant sensor measurements against their average. A variety of averaging techniques are available, including:

- **Simple Averaging** – Simple averaging involves adding the values of the signals at each instant of time and dividing the sum by the number of signals.
- **Band Averaging** – Band averaging uses a band to reject outliers and averages the values of the remaining signals at each instant of time.
- **Weighted Averaging** – Weighted averaging applies a set of fixed multipliers to the signals prior to averaging. For example, weights could be determined based on how far they deviate from the simple average.
- **Parity Space** – In parity space, each signal is weighted based on how many other signals share the parity space band with the signal. This weighted measure is commonly referred to as consistency, and requires the determination of a consistency check value which dictates the sensitivity of the parity space estimate to individual signal values which deviate from each other.

These averaging techniques are illustrated in Figure 14.



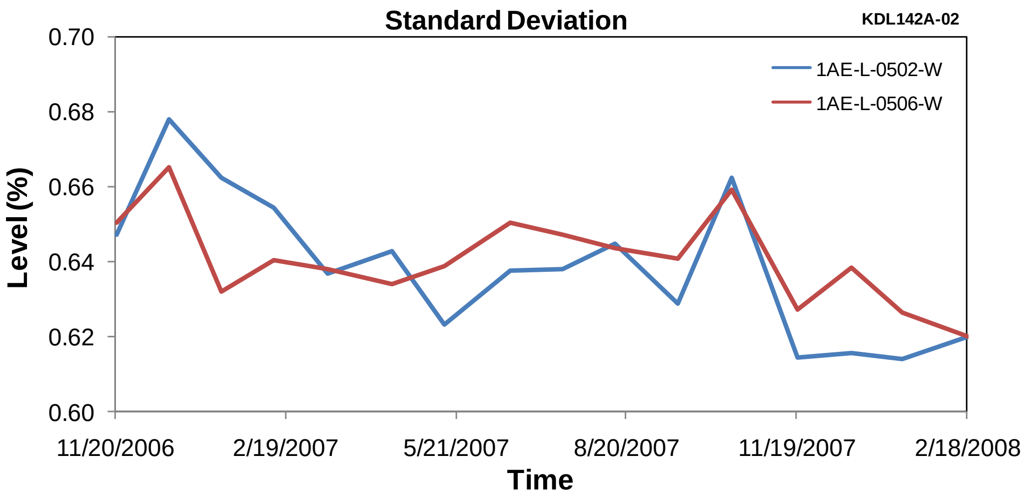


Figure 13: Statistical trending of static OLM data

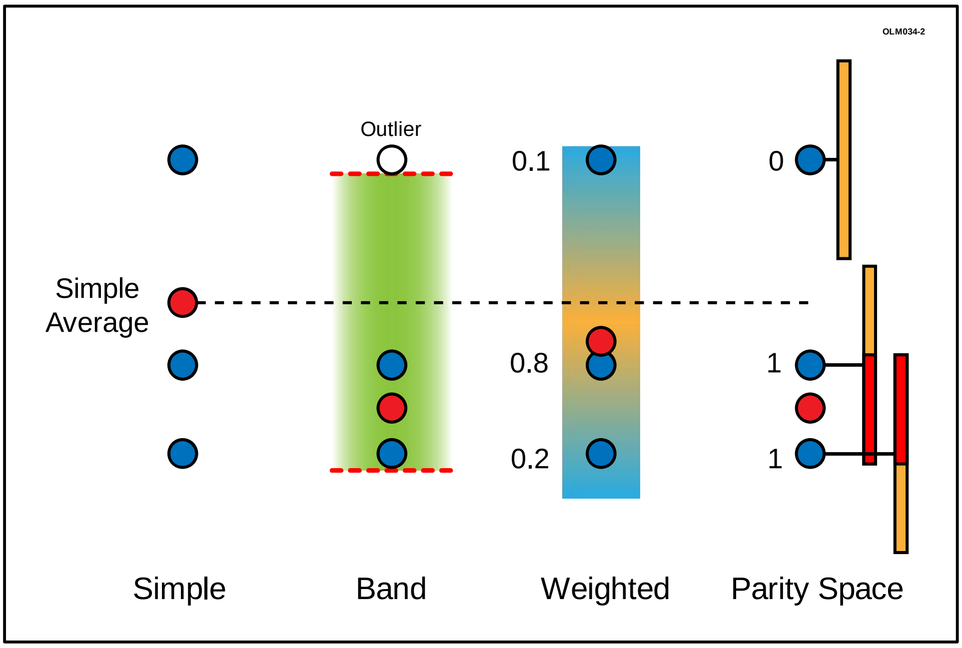


Figure 14: Redundant sensor averaging techniques

3.1.3 <u>Detecting deviation from average</u>

Once the parameter estimate is calculated using an averaging technique, the deviations of each individual sensor in the redundant group from this estimate are computed. For transmitter calibration monitoring, these deviations are analyzed over an entire fuel cycle and checked against deviation limits that are established such that if the sensor deviations reside within the limits, then the sensor is determined to be within calibration. Sensors are classified as being in need of calibration when their respective deviations exceed the deviation limits. Note that the deviation limits must be specifically derived for on-line calibration monitoring and differ from the manual as-found and as-left calibration limits.

Figure 15 presents an illustration of a deviation analysis for four reactor coolant system (RCS) flow transmitters. The y-axis in this figure is the difference between the reading of each transmitter from the parity space average estimate, and the x-axis represents time in months. The data is shown for a period of 74 months during which the plant was operating. None of the four signals show any significant drift during the 74-month period and remain within the deviation limits. That is, these transmitters have not suffered any significant calibration change and do not need to be calibrated.

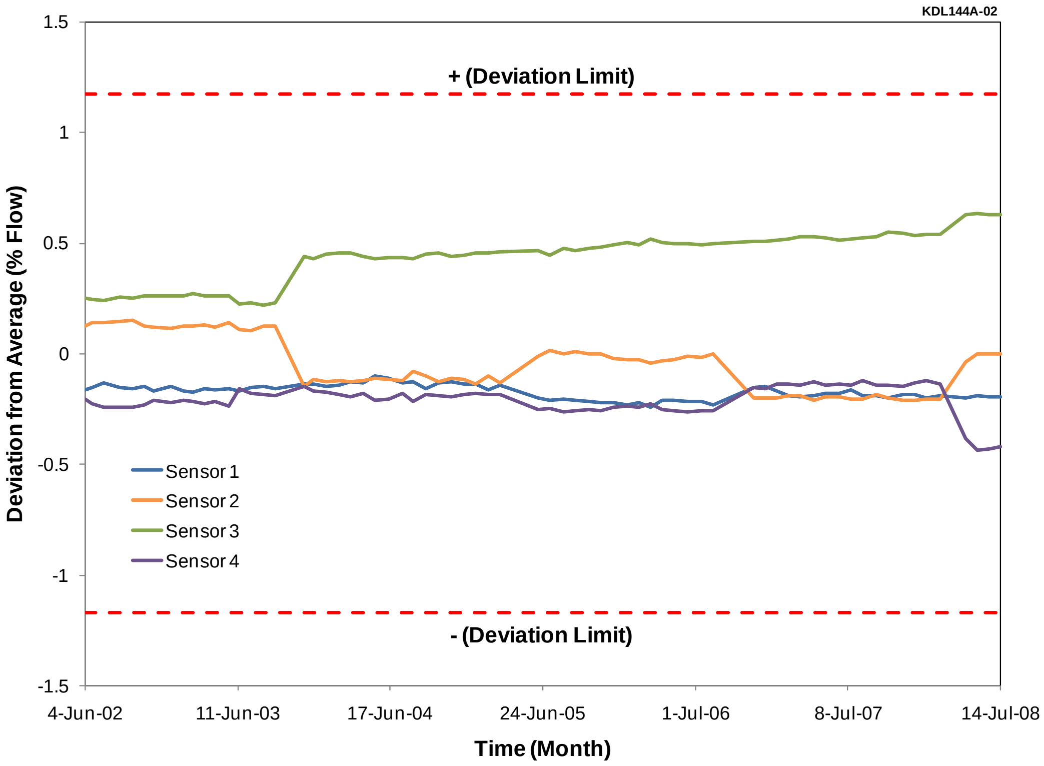


Figure 15: On-line calibration monitoring data for four RCS flow transmitters in a nuclear power plant

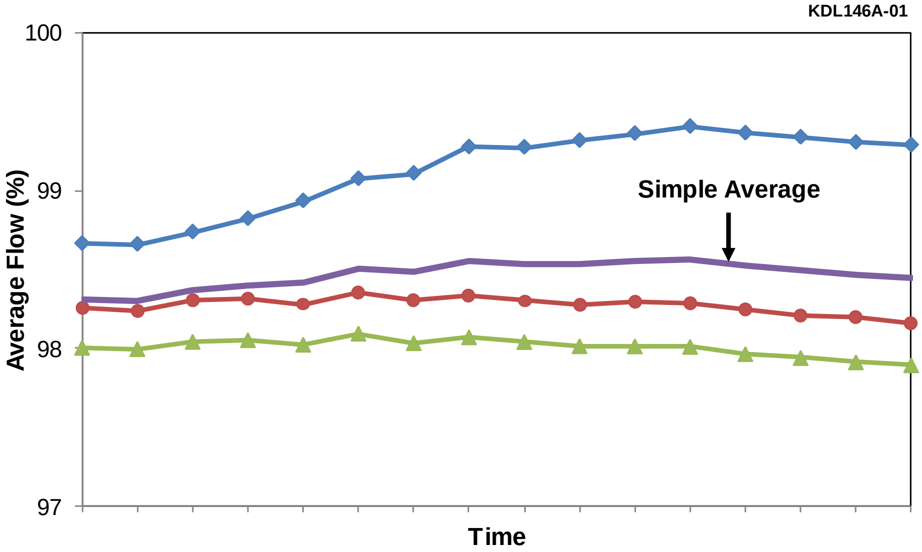
Figure 16 (a) shows data from three flow transmitters. The average of the three transmitters is plotted as a solid line. As shown in Figure 16 (a), the top transmitter appears to be drifting upwards, which is subsequently causing the average of the three transmitters to drift upwards as well. As a consequence, the deviation of the bottom transmitter exceeds the lower deviation limit as shown in Figure 16 (b), although it is clearly not drifting in Figure 16 (a).

Figure 17 (a) shows the same transmitters that were shown in Figure 16 plotted with an average calculated by using the parity space technique. The parity space technique effectively removes drifting sensors so that the average is not affected.

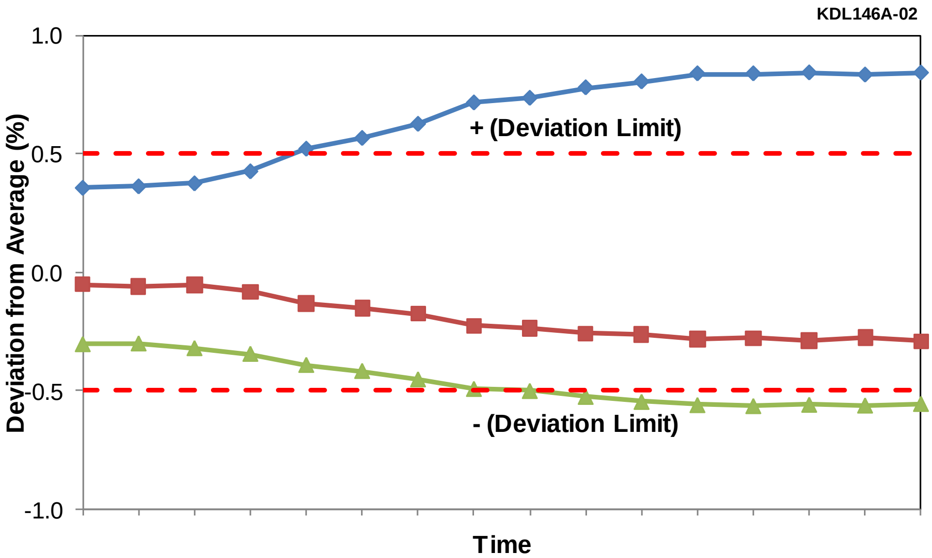
As shown in Figure 17 (a), the parity space technique rejects the top sensor when it has drifted too far away from the bottom two sensors. As a result, the deviations of the bottom two transmitters remain within the deviation limits as shown Figure 17 (b).

3.1.4 <u>Physical modeling</u>

Physical modeling techniques use the mathematical relationships between parameters to detect process or sensor anomalies. These relationships are based on first principal equations such as heat and mass balance equations, steady-state thermodynamics, transient thermodynamics and fluid dynamics. The application of physical modeling may be as simple as calculating a mass-flow balance equation or as involved as



(a) Raw Data with Simple Average



(b) Deviation from Simple Average

Figure 16: Effect of spillover on deviations from the average of redundant sensors

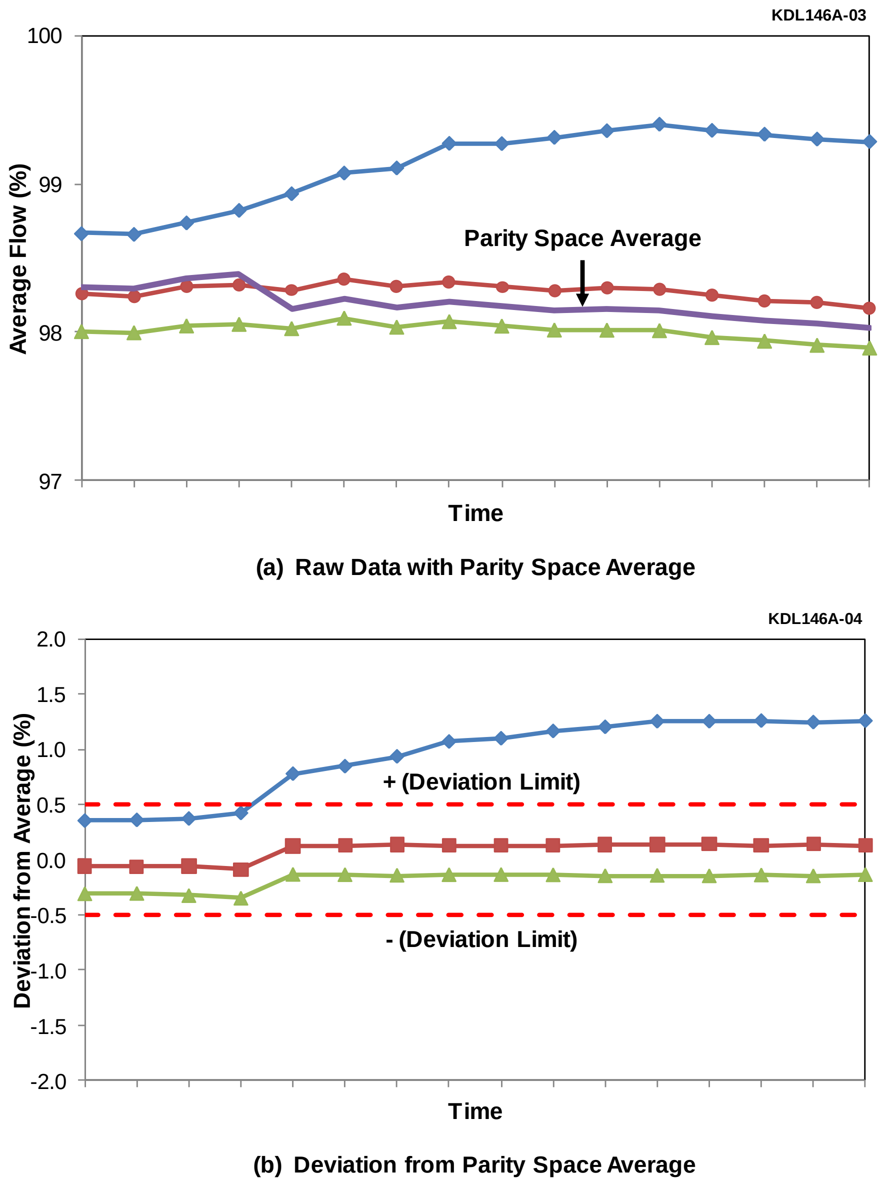


Figure 17: Average of redundant sensors using the parity space technique

describing the complex mathematical relationships between nuclear power plant components such as a turbine, heat exchanger, condenser, pump, valve, mixer, diffuser, etc. Physical modeling involves inputting process parameter measurements into mathematical equations, and determining sensor or process anomalies by subtracting the outputs of the model from the inputs to form *residuals* (Figure 18). Residuals from physical models should be near zero when the plant parameters are normal.

The main requirement for physical modeling is that the structure, design, and function of the modeled process or component is well known and can be accurately described in mathematical equations. The availability of efficient computational methods for solving the particular type of equations employed in the physical modeling is also a primary requirement.

3.1.5 Empirical modeling

In contrast to physical models, empirical modeling techniques attempt to define relationships between variables based only on the data itself, and not on the physical properties of the variables that are being compared. As such, empirical models do not require as much of an in-depth knowledge of the plant and as a result, may be easier to implement and maintain than physical models.

The most common empirical modeling techniques are generally separated into two main categories, namely *parametric* models and *non-parametric* models. These types of empirical models are illustrated using a 1-Dimensional data set (Table 1) for simplicity.

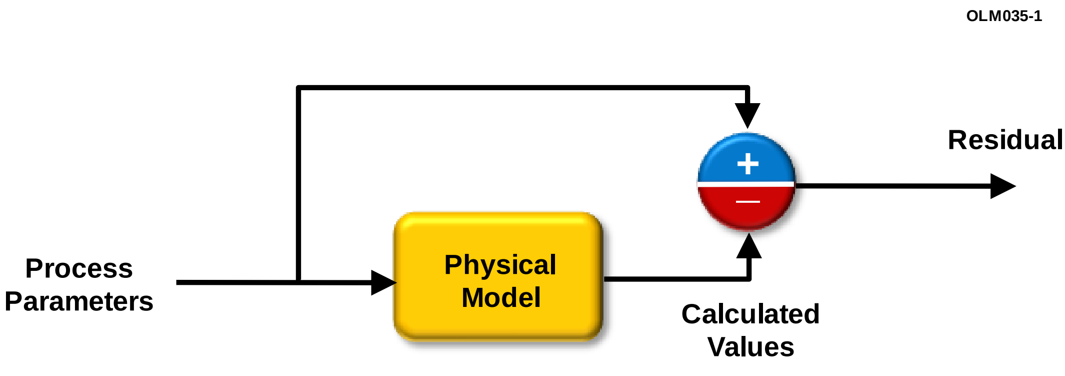


Figure 18: Physical modeling process

Table 1: Example 1-dimensional data set

X Value	2	10	20	40	80	97
Y Value	3.6	18.0	54.0	186.0	690.0	1001.1

Parametric empirical models

In parametric empirical models, the mathematical structure of the model is pre-defined, such as in an equation, and the example data are fit to the pre-defined structure. For example, suppose the example data set from Table 1 is assumed to follow a polynomial model defined by:

$$y_t = a_0 + a_1 x_t + a_2 x_t^2 \qquad (3)$$

where y_t is the output at sample t, x_t is the input at sample t, and a_0, a_1, and a_2 are the coefficients of the equations which are unknown. The object of parametric modeling is to use the example data to find the coefficients a_0, a_1, and a_2 that best fit the data. Figure 19 shows the 6 sample X-Y value pairs denoted by solid circles. Inputting the X-Y pairs into a polynomial results in the coefficients $a_0 = 2.0$, $a_1 = 0.6$, and $a_2 = 0.1$. Figure 19 shows the original training points and the curve defined by the coefficients a_0, a_1, and a_2. As shown in the figure, the polynomial model fits the data very well.

One of the major problems with parametric modeling is that most of the time, the mathematical structure of the example data is not always known. In the case of this example, the fact that the data should follow a 2nd order polynomial was known beforehand, and as a result, the parametric model fit the training data very well. However, it is rarely the case in practice that the exact relationship between variables is known, especially when dealing with complex relationships between processes in nuclear power plants. With parametric modeling, the best that can be done is to make an educated guess at the underlying structure of the data and then modify the model until the model fits the example data to some desired accuracy.

Neural networks are a class of parametric models that have been used for static OLM applications in nuclear power plants [Hashemian, 1995; Hashemian et al., 1998; Hines, 2006].

Non-parametric empirical models

In a non-parametric empirical model, the mathematical structure is not implied beforehand. Instead, training examples are stored in memory, and each new data sample is compared to the training examples to calculate a best estimate. Unlike parametric modeling, non-parametric models are not restricted to a pre-defined relationship between the inputs and outputs.

In non-parametric models, the example data is all that the non-parametric model ‘knows’. Non-parametric models do not assume the data is restricted to underlying structure (like a parametric model). For example, given the data from

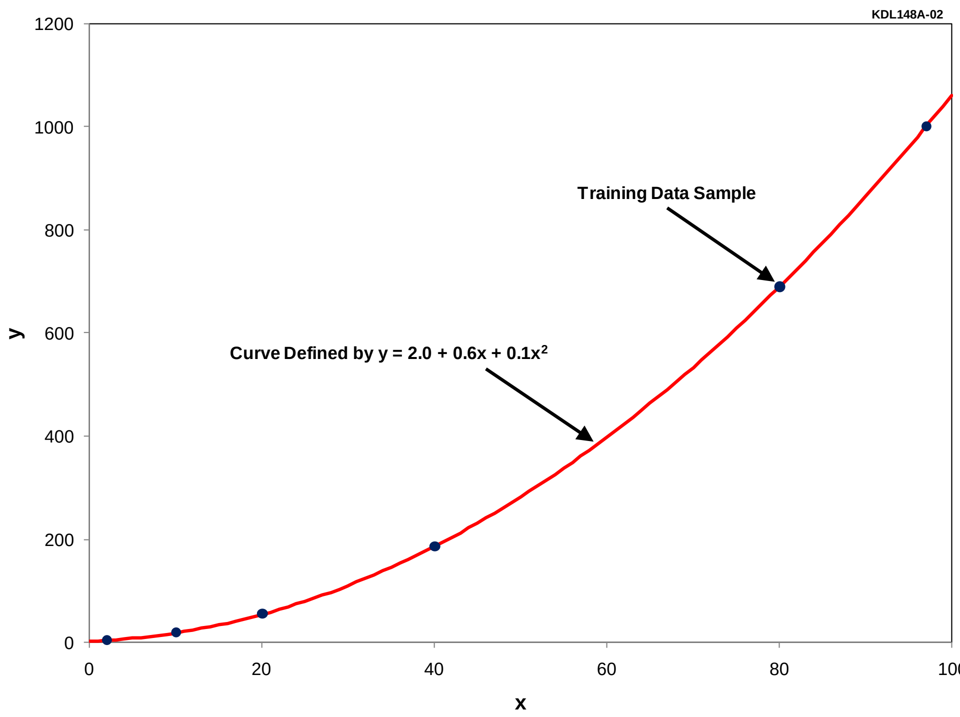


Figure 19: Parametric model of the example data points

Table 1, a non-parametric model would only 'know' that an X value of '2' is associated with a Y value of '3.6', an X value of '10' is associated with a Y value of '18.0', and so on. When a non-parametric model is presented with new data, it calculates a new estimate based solely on the training examples

Figure 20 shows non-parametric model estimates for X values 1 through 100 given the training data in Table 1.

Figure 20 shows that the non-parametric model estimates agree closely with the ideal curve from which the training data was taken. Note that non-parametric modeling may not estimate well in areas that do not have training data (in Figure 20, see the estimates for X values 20 through 40). This is why it is important with non-parametric models to carefully choose training data that spans the data effectively.

The multivariate state estimation technique (MSET) and kernel regression are two non-parametric methods that have been used with success to model data in nuclear power plants [Hines, 2006; Hashemian 2006].

3.2 Dynamic OLM analysis

Dynamic analysis of nuclear plant sensors and equipment is concerned with determining how sensors and equipment react to fast-changing events such as temperature or pressure steps, ramps, spikes, etc. Dynamic analysis is most often divided into frequency and time domain analysis. Methods for dynamic analysis, unlike static modeling methods, are well-understood and have been used for decades in the nuclear industry.

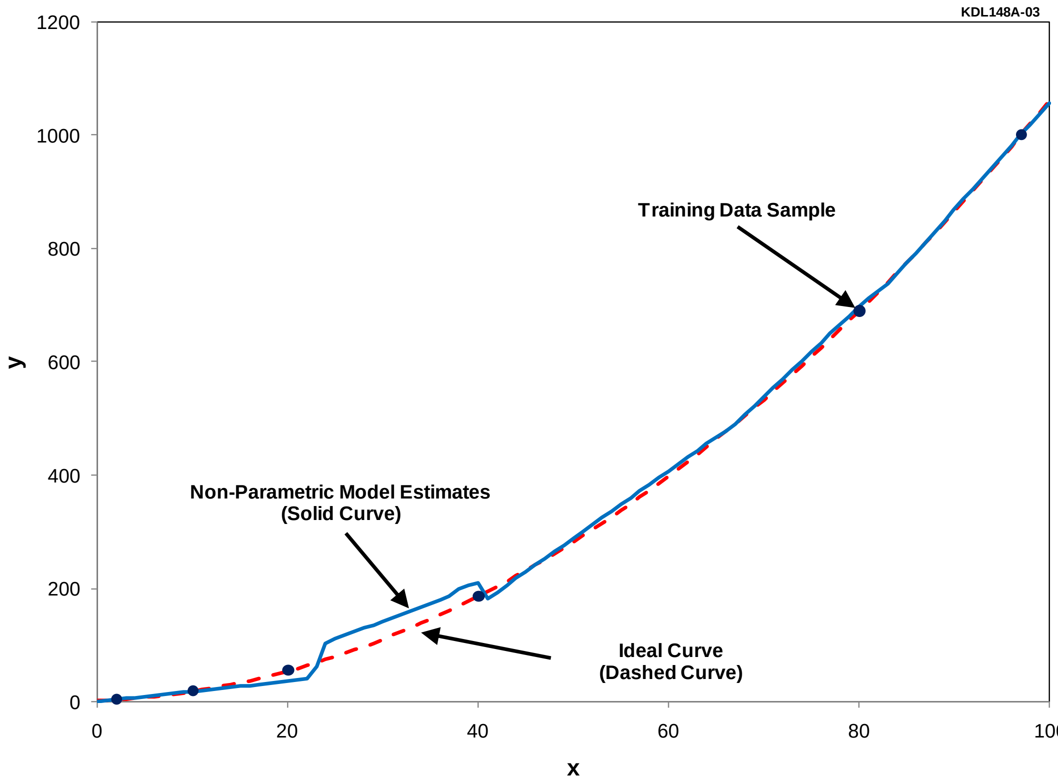


Figure 20: Non-parametric model estimates

3.2.1 Frequency domain analysis

In frequency-domain analysis, the spectrum of the data is calculated using a technique such as the FFT. Figure 21 shows the spectrum of the noise signal from a sensor in a nuclear power plant. Note that the spectrum is shown in terms of the auto power spectral density (APSD). The APSD is the variance of the signal within a small frequency band as a function of frequency plotted against frequency. For a simple first-order system, the APSD is all that may be needed to provide the sensor's dynamic response or response time. In this case, the response time is determined by measuring the break frequency (F_b) of the APSD, as shown in Figure 22. However, process sensors are not necessarily first order, and APSD plots from actual process signals are not smooth enough to allow one to measure the break frequency as simply as shown in Figure 22. In fact, APSDs often contain resonances and other process effects that complicate the process of determining a response time by analyzing the APSD. As such, APSD analysis experience is often needed to determine a sensor's response time by using the noise analysis technique. For example, a dynamic model of the sensor is used with the APSD plot in order to obtain the sensor's response time. The model, which is normally a frequency-domain equation, is fit to the APSD to yield the model parameters. These parameters are then used in the model to calculate the sensor's response time. Figure 23 shows an example APSD and the model fit to the APSD for a pressure sensor in an operating nuclear power plant.

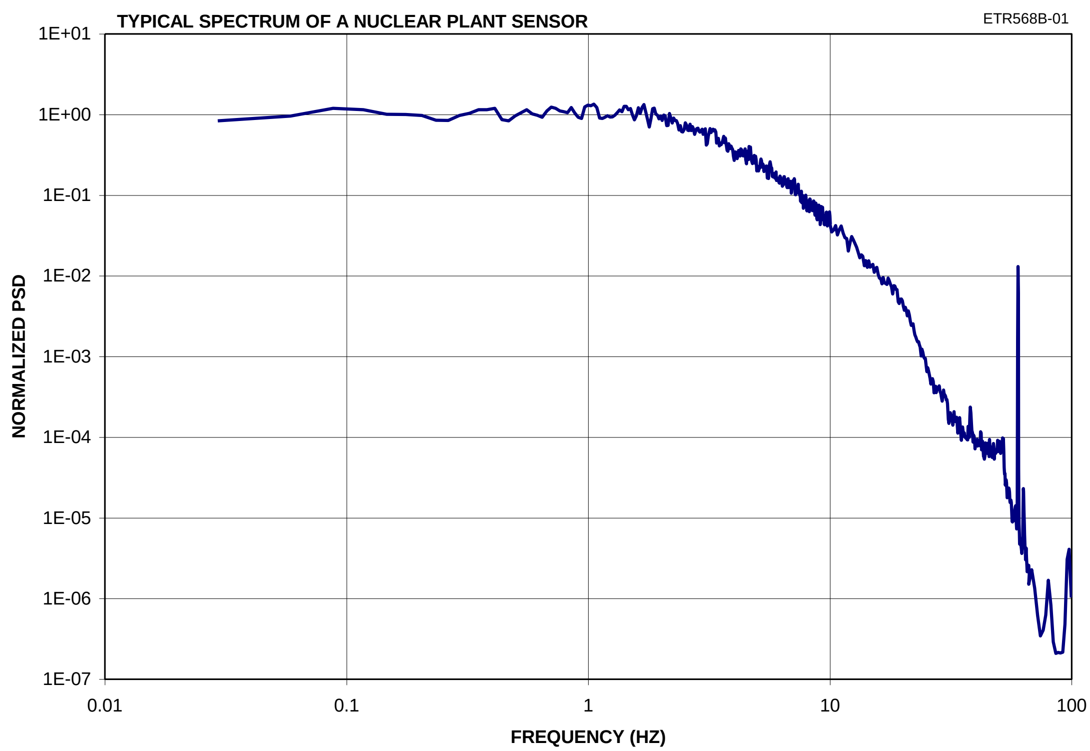


Figure 21: **A**PSD of a typical nuclear power plant sensor

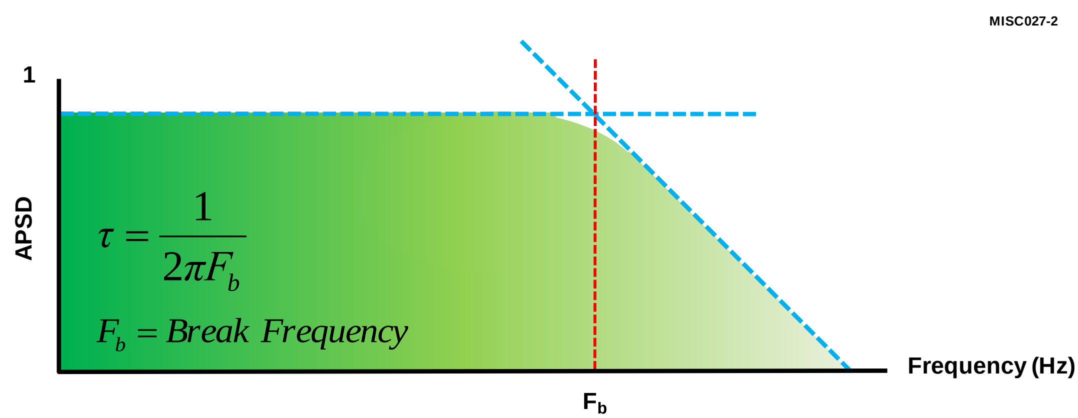


Figure 22: First-order system APSD

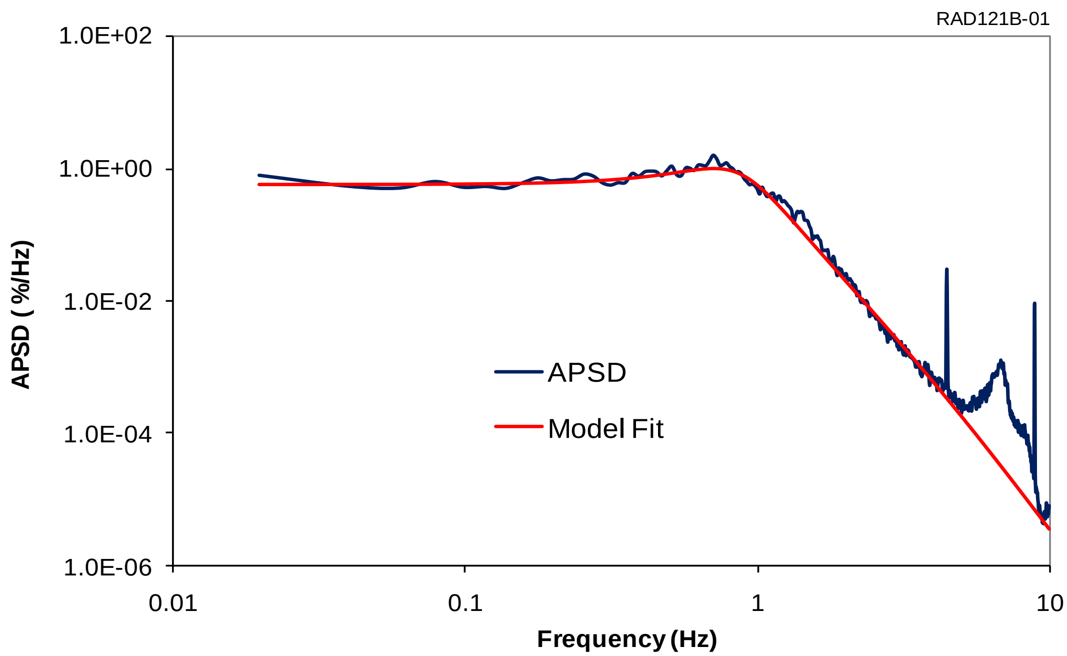


Figure 23: Sensor APSD and model fit to APSD

The procedure for analyzing noise data in the frequency domain is illustrated in Figure 24. This analysis involves performing an FFT on the sensor's output signal in order to obtain its APSD. A function (i.e., sensor model) is then fit to the APSD and the parameters of the function are identified and used to calculate the sensor's response time.

3.2.2 Time domain analysis

In the time domain, correlation and autoregressive methods are used for analysis of noise data. The correlation function for a noise signal *x(t)* is written as:

$$R_{xx}(\tau) = \frac{1}{T}\int_{-T/2}^{T/2} x(t)x(t-\tau)dt \tag{4}$$

where $R_{xx}(\tau)$ is referred to as autocorrelation function, τ is a time lag, and T is the signal duration. The autocorrelation function describes the general dependence of the value of the data at one time on the values at another time. The function provides insight into the existence of periodic signal components in the random data and the nature of narrow and wideband noise properties. In order to obtain the correlation between two different signals *x(t)* and *y(t)*, a function called cross-correlation is used. The cross-correlation function $R_{xy}(\tau)$ is written as:

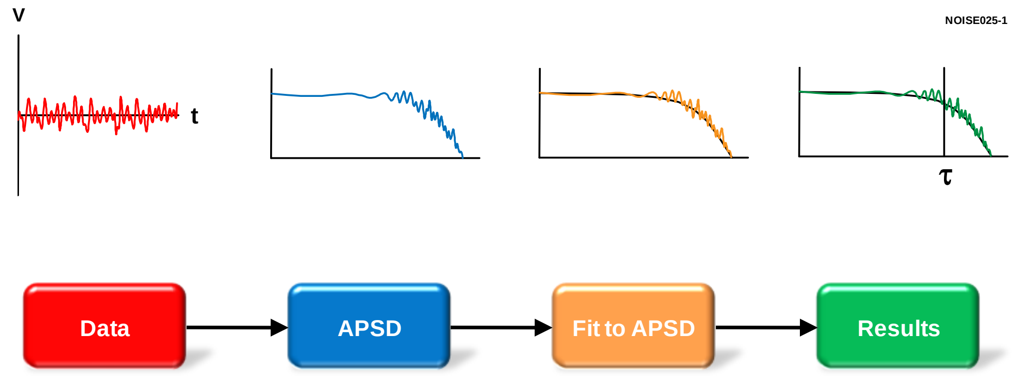


Figure 24: Frequency domain analysis procedure

$$R_{xy}(\tau) = \frac{1}{T}\int_{-T/2}^{T/2} x(t)y(t-\tau)dt \qquad (5)$$

The cross-correlation function describes the general dependence of the values of one set of data on the other. It is used for measurement of time lags in transport processes, determination of transmission path by observing multiple peaks in $R_{xy}(\tau)$, and detection and elimination of interfering noise. In the time domain analysis of sensor noise data, the correlation function is plotted versus time. The peak in the correlation plot identifies the time delay between the sensors, i.e. the propagation time of the noise between the two sensors. Figure 25 illustrates the result of the cross-correlation of a pair of signals from two sensors in a nuclear power plant.

4. OLM Implementation Requirements for Existing Reactors

Most of the existing nuclear power plants have the capabilities and equipment that are needed for implementing many of the OLM technologies discussed in this paper. However, for most plants, these capabilities are not used to their fullest extent for OLM applications. This section addresses the various requirements for implementing OLM technologies in existing generation of nuclear power plants.

4.1 Data acquisition for static applications

4.1.1 Source of data

OLM technologies are dependent on the amount of data that can be readily accessed. In most existing nuclear power plants, data from the sensors needed for the static OLM applications is available from the plant computer. However, depending on the type of static OLM application being developed, additional sensor data may be needed. Table 2 lists examples of the plant services that need to be measured in order to implement the OLM technologies discussed in this paper.

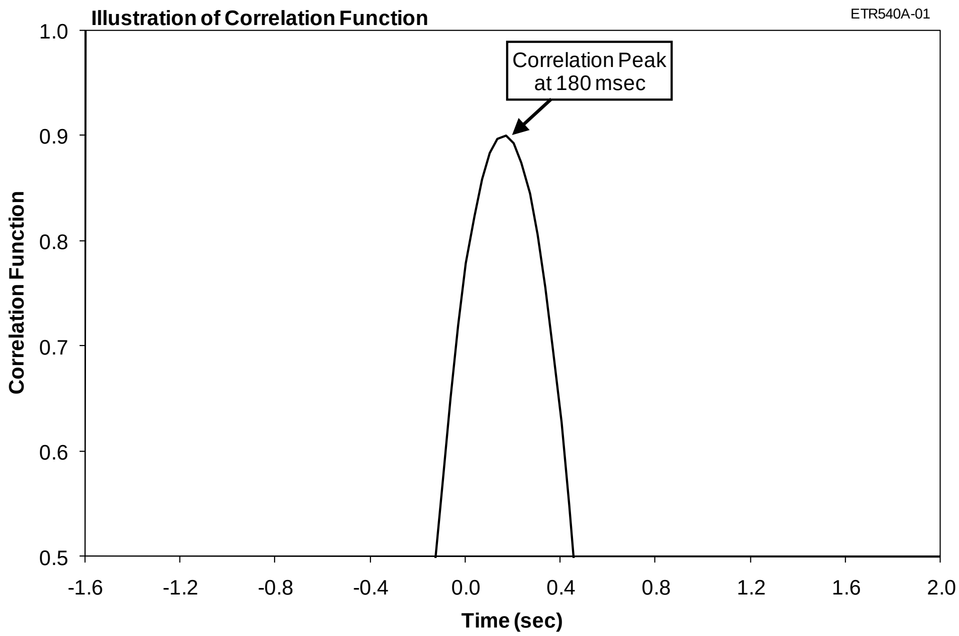


Figure 25: Plot of correlation function of a pair of signals from two sensors in a nuclear power plant

It should be noted in Table 2 that the services included for calibration monitoring are typically those that have at least two redundant sensors.

For cross-calibration, the services include the hot leg and cold leg temperatures which are measured by redundant resistance temperature detectors (RTDs). This list includes both the narrow range and wide range RTDs. Also included in cross-calibration are the core exit temperatures, which are typically measured by thermocouples.

The list of services for equipment condition assessment includes the typical services that have been used in implementations in the past, and is not an exhaustive list of services that can be monitored. In fact, virtually any service that can be measured can be used for monitoring the performance of some plant system or some piece of equipment.

4.1.2 <u>Plant conditions</u>

Static OLM applications generally use data during startup, steady-state, and shutdown periods as illustrated in Figure 26. However, experience with implementing OLM in nuclear plants has shown that some services in PWRs, such as refueling water storage tank (RWST) level, may transition through their calibrated ranges during the refueling outages (depending on when the tank is drained and/or filled). As such, it is recommended that plants consider retrieving data during outages as well as the normal periods of plant operation.

Table 2: Sources of static OLM data

Service	OLM Static Analysis Applications		
	Calibration Monitoring	**Cross-Calibration**	**Equipment Condition Assessment**
Reactor Coolant System Flow	✓		✓
Steam Generator Level	✓		✓
Pressurizer Level	✓		✓
Pressurizer Pressure	✓		✓
Steam Generator Pressure	✓		✓
Steam Flow	✓		✓
Feedwater Flow	✓		✓
Turbine Impulse Pressure	✓		✓
Reactor Building Pressure	✓		✓
Reactor Coolant System Pressure	✓		✓
Refueling Water Storage Tank Level	✓		✓
Reactor Coolant System Hot Leg Temp		✓	✓
Reactor Coolant System Cold Leg Temp		✓	✓
Core Exit Temperature		✓	✓
Reactor Coolant Pump Seal Injection Flow			✓
Volume Control Tank Level			✓
Chemical Volume Control System Letdown Flow			✓
Chemical Volume Control System Charging Flow			✓
Reactor Power			✓
Generator Output			✓
Feedwater Temperature			✓
Condenser Pressure			✓
Reheater Outlet Temperature			✓
Condenser Cooling Water Inlet Temperature			✓

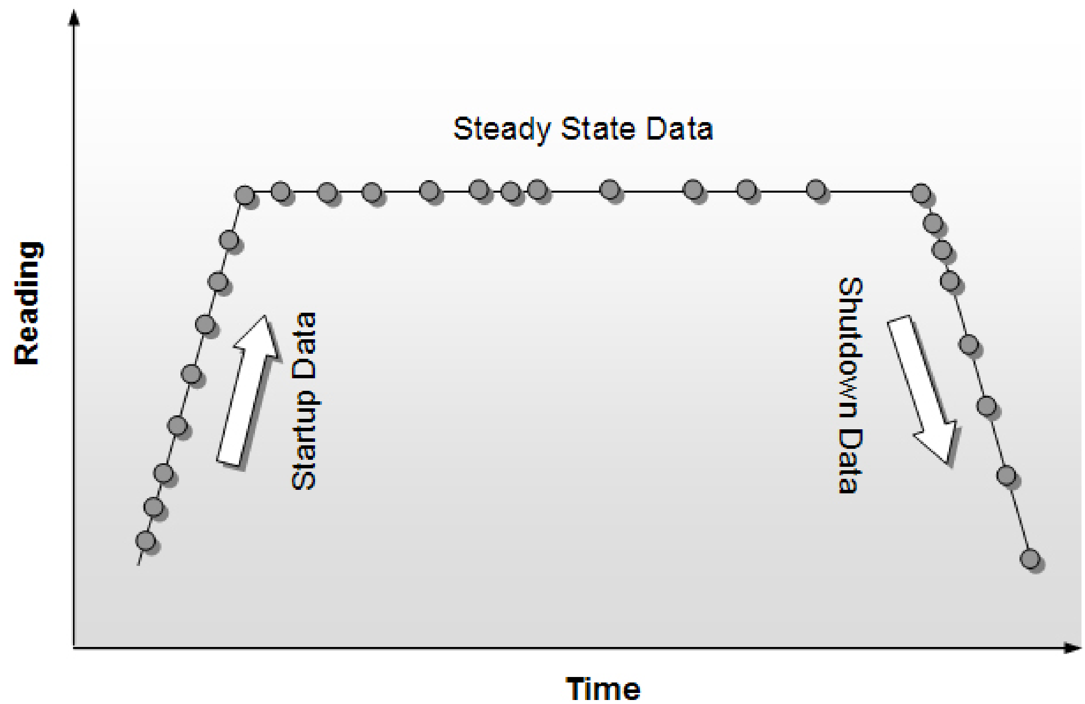


Figure 26: Three regions of OLM data: startup, steady-state, and shutdown

4.1.3 <u>Sampling frequency</u>

The sampling frequency or sample period for OLM data in existing generation of nuclear power plants is typically limited to the maximum sample rate of the data that is supplied to the plant computer. For example, data is sent to the plant computer every 30 seconds. In these cases, data should be sampled for longer periods of time to obtain a sufficient number of samples. Table 3 lists the minimum sampling rate requirements for the OLM applications discussed in this paper.

As noted in Table 3, the sample period for calibration monitoring ranges from 10 to 60 seconds. The sample period will depend on how the data for calibration monitoring is analyzed. For example, if the OLM algorithm for calibration monitoring only includes steady-state operation data, then a sample period of 60 seconds is sufficient.[6] However, if the OLM algorithm includes periods of startup and shutdown transients, then a shorter sample period is recommended. Experience has shown that a sample period of 10 seconds is sufficient for monitoring the startup and shutdown transients of most critical nuclear plant processes for calibration monitoring [EPRI, 2006].

Table 3: Sample period requirements for static OLM techniques

OLM Application	Sample Period
Pressure Transmitter Calibration Monitoring	10 – 60 sec.
RTD and CET Cross-Calibration	1 – 10 sec.
Equipment Condition Assessment	60 sec.

4.1.4 Data resolution requirements

The plant computers in most nuclear power plants are capable of acquiring sensor data at a 12-bit resolution [Hashemian, 2007]. For most static OLM applications, such as the ones discussed in this paper, a 12-bit resolution is sufficient. The biggest issue with resolution for static OLM analysis is the compression setting of the historian. As previously mentioned, historians typically have two types of compression parameters to determine if data is stored or not: one parameter to set the minimum change from the previous value (usually expressed in % range of the sensor); and one parameter for the maximum time that can elapse between measurements. It is recommended that the plant turn off the compression settings entirely or at least be capable of turning them off for the period when OLM data is acquired. At a minimum, the setting for the minimum time that can elapse must be less than or equal to the required sample rate. Table 4 lists the compression settings required for each type of static OLM analysis.

4.1.5 Data storage requirements

The storage requirements for static OLM analysis depend on the sampling rate required for the type of analysis, the amount of time that is being recorded, and the number of sensors needed for a particular application. Table 5 lists the recommended minimum storage requirements for the static OLM applications discussed in this paper. Note that in Table 5, the sample period for calibration monitoring has been shortened to 1 second for conservatism. Data storage requirements in Table 5 are listed in terms of gigabytes (GB).

Table 4: Compression setting requirements for static OLM techniques

OLM Technology	Maximum Time Between Samples
Calibration Monitoring	10 – 60 sec.
Cross-Calibration	1 – 10 sec.
Equipment Condition Assessment	60 sec.

Table 5: Minimum storage requirements for static OLM techniques per fuel cycle

OLM Technology	Sampling Period	Length Stored	Number of Sensors	Required Storage (GB)
Calibration Monitoring (Steady-State)	1 sec.	12 hours/month x18 months	60	0.5
Calibration Monitoring (Startup, Shutdown, Outage)	1 sec.	20 – 40 days	60	2.0
Cross-Calibration	1 sec.	6 hours	75	0.25
Equipment Condition Assessment	60 sec.	12 hours/month x 18 months	200	0.25

The storage requirements in Table 5 assume that each measurement consists of a 4-byte measurement value and a 4-byte timestamp, for a total of 8 bytes per measurement.

4.1.6 Hardware requirements

Most of the static analysis OLM technologies will get their data from the plant computer. As such, no special hardware is required. However, for those cases where measurements must be taken from the instrumentation cabinets, the following specifications are recommended:

- Input impedance : 1M Ohms
- Channel-to-channel isolation: 1G Ohms 250 VRMS continuous
- Earth-to-ground isolation: 1000 VRMS continuous

For cross-calibration, spare RTDs need a current bridge and an A/D converter to gather or supply data to the plant computer.

4.2 Data analysis requirements for static applications

4.2.1 Static data qualification

One of the most important aspects of data qualification is the cleaning of data before it is analyzed. Plant computer data frequently has bad data points and they must be removed before analysis can begin. At a minimum, the following problems should be checked for and removed from data:

- Stuck Data
- Transients
- Missing Data
- Spikes and Outliers

Software programs that can automatically remove the bad data are recommended, but these removals can also be done manually. After the data is properly cleaned, the following basic statistics and data quality factors should be checked for each sensor's data:

- Mean Value
- Standard Deviation or Variance
- Skewness
- Kurtosis
- Amplitude Probability Density (optional)
- Lag Plot (optional)

Checking these statistics against normal values can often indicate problems before any rigorous analysis begins.

4.2.2 Static data analysis

Static OLM data analysis is most concerned with the type of algorithm that will be used to do the analysis. Table 6 lists the OLM technologies and the types of algorithms that can be used for each technology.

4.3 Data acquisition requirements for dynamic applications

4.3.1 Source of data

The sensors required for dynamic OLM analysis will depend on the type of analysis that is being conducted. Table 7 lists the typical sensors involved with each type for dynamic OLM analysis that is discussed in this paper.

Table 6: Algorithms for static OLM analysis

OLM Application	Required Algorithm
Pressure Transmitter Calibration Monitoring	Averaging, Physical Modeling, Empirical Modeling
RTD and CET Cross-Calibration	Averaging
Equipment Condition Assessment	Physical Modeling, Empirical Modeling

4.3.2 Plant conditions

For most of the dynamic OLM analysis techniques, the plant should be in steady-state operation at 80% power or greater. This is because at lower power levels, the fluctuations in the signals become difficult to measure.

4.3.3 Sampling frequency

For most dynamic OLM analysis techniques, a sampling rate of 1 kHz is sufficient. For some applications like dynamic response calculation, the data from different sensors does not necessarily have to be taken simultaneously. However, for applications such as reactor internals and core flow anomaly detection, it is important that the data is taken simultaneously for inter-signal comparisons.

4.3.4 Data resolution requirements

While plant computer data has adequate signal resolution for most static applications (12-bit), it is normally not sufficient for dynamic OLM applications. As such, dynamic OLM applications need special data acquisition with greater digital signal resolution. As shown in Figure 27, there is very useful dynamic response information at both higher frequencies and lower signal resolutions than is available from typical plant computer data. Most of the dynamic analysis data can be analyzed if taken with a 24-bit resolution. However, if a 24-bit A/D is not available, then a gain stage and offset circuit needs to be used to achieve adequate resolution.

4.3.5 Data storage requirements

Table 8 shows the minimum storage requirements for dynamic data analysis.

As in the static OLM application storage requirements, the requirements in Table 8 assume that the data values are stored in 4 bytes, with another 4 bytes for a timestamp. For the neutron detector life extension and dynamic response methods, a timestamp is not necessary; however, it is included in this table for conservatism.

Table 7: Sensors for dynamic OLM analysis

Service	OLM Dynamic Analysis Applications			
	Dynamic Response	**Reactor Internals**	**Core Flow Anomalies**	**Neutron Detectors**
Reactor Coolant System Flow	✓			
Steam Generator Level	✓			
Pressurizer Level	✓			
Pressurizer Pressure	✓			
Steam Generator Pressure	✓			
Steam Flow	✓			
Feedwater Flow	✓			
Reactor Coolant System Pressure	✓			
Reactor Coolant System Hot Leg Temp	✓		✓	
Reactor Coolant System Cold Leg Temp	✓			
Core Exit Temperature		✓	✓	
Reactor Power		✓	✓	✓
Reactor Vessel Level Indication System (RVLIS) Delta Pressure			✓	
In Core Temperature		✓	✓	
In Core Detectors		✓	✓	✓

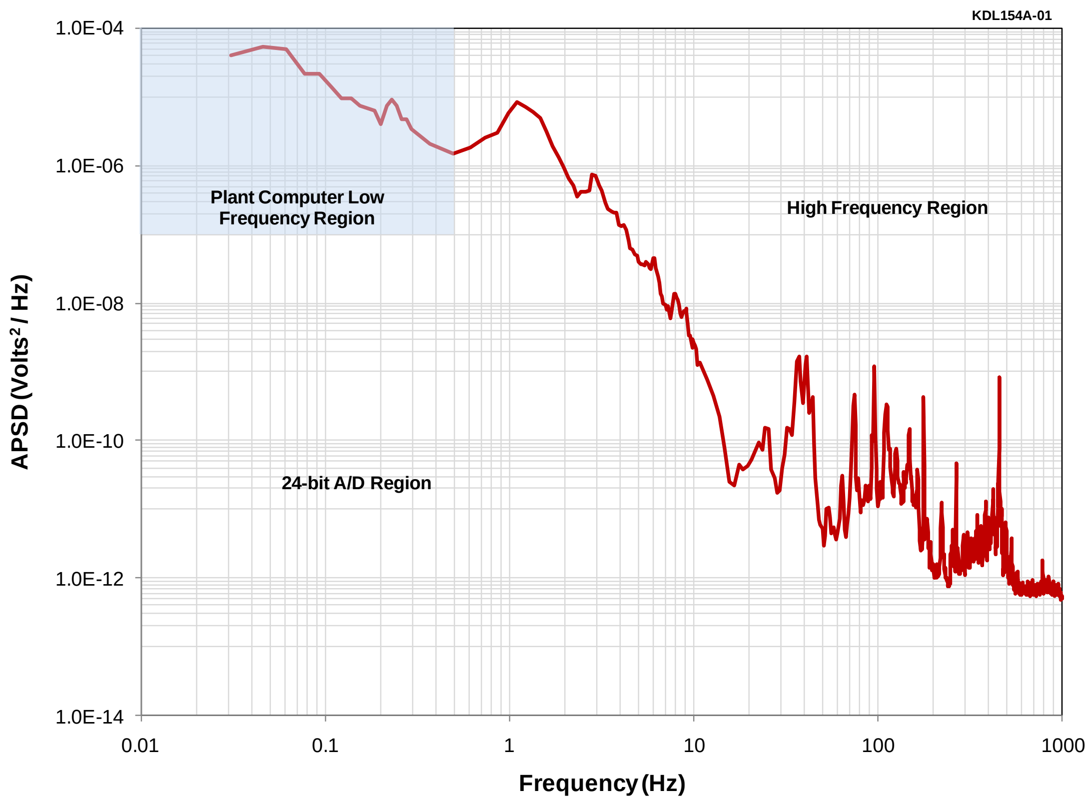


Figure 27: APSD Example of Low Frequency (Plant Computer) and High Frequency Data Acquisition

4.3.6 <u>Hardware requirements</u>

Because most plant computers in nuclear power plants do not have the capability of sampling at rates that are required for dynamic analysis, the data will have to be taken with a separate data acquisition system. Like the dedicated data acquisition system for static analysis, the dynamic data acquisition system will have to be isolated.

There are many ways to obtain high frequency data. The high-frequency data acquisition equipment will have the following general requirements as shown in Figure 28:

1) Isolation
2) Low Pass Filter (for anti-aliasing)
3) Analog-to-Digital Converter
4) Computer (to acquire data)
5) Data Storage

Table 8: Storage requirements for dynamic OLM analysis

OLM Application	Sample Rate	Length Stored	Number of Sensors	Required Storage (GB)
Dynamic Response Measurements	1 kHz	30 minutes	200	3.0
Reactor Internals Vibration	100 Hz	6-12 Hours	80	3.0
Core Flow Anomaly Detection	1 kHz	6-12 Hours	80	25.0
Neutron Detector Life Extension	1 kHz	30 minutes	8-16	0.25

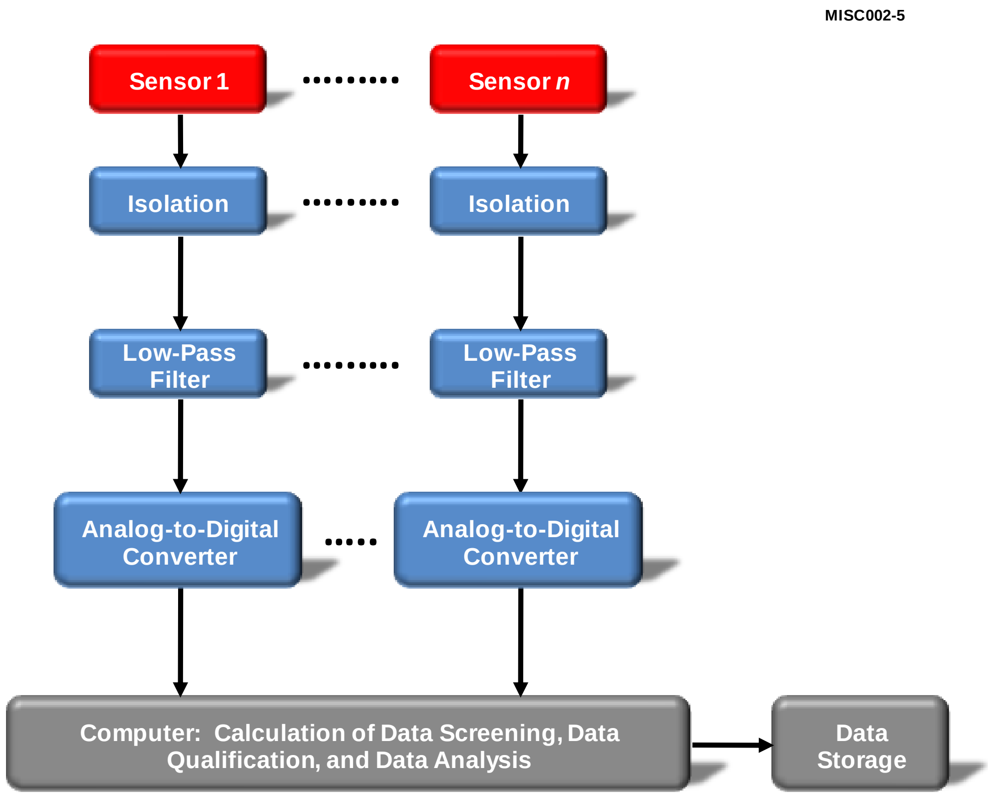


Figure 28: Block diagram of high frequency data acquisition system with 24-bit A/D Converter

Many signals need to be measured down to the microvolt range. This can be achieved today with 24-bit A/D converters. Alternatively, if the A/D resolution is only 12- or 16-bit, then the following additional equipment as shown in Figure 29 may be necessary:

1) Gain Amplifier
2) Sample and Hold
3) Digital-to-Analog Converter
4) DC Offset Circuit

These equipment all need to be evaluated on an individual basis for each application to cover the dynamic signal ranges and specific isolation requirements for each plant.

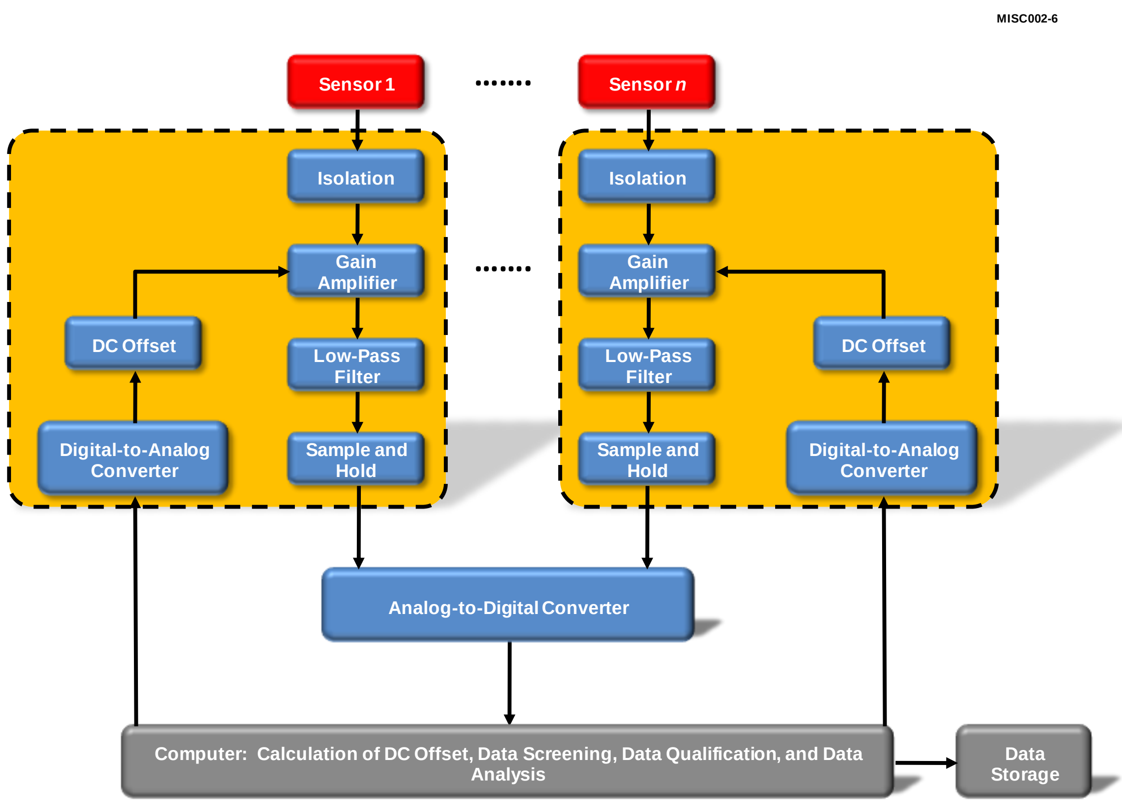


Figure 29: Block diagram of high frequency data acquisition system with gain and DC offset

4.4 Data analysis requirements for dynamic applications

4.4.1 Dynamic data qualification

For dynamic OLM analysis, data qualification is concerned with ensuring that the data is Gaussian. At a minimum, the following statistical properties need to be examined:

- APD Plot
- Variance
- Skewness
- Kurtosis

These parameters are useful for determining if the data is Gaussian, and for recognizing changes when compared against previous measurements.

4.4.2 Dynamic data analysis

For dynamic data analysis, some form of time-based and frequency-based analysis must be used. For dynamic response, frequency-based analysis involving calculation of the APSD is probably the most important; however, time-based algorithms such as auto-regressive modeling (AR) are also important to double-check the frequency domain results. It is also helpful to have baseline measurements and APSDs for dynamic analysis. This provides the simplest way to compare previous and current results for evidence of changes.

5. OLM Implementation Requirements for New Reactor Designs

Reactor designs for the next generation of nuclear power plants typically incorporate an integrated digital infrastructure including highly-integrated control rooms, fault-tolerant control systems, and monitoring systems with large amounts of available information and data. Most of these digital systems are designed to monitor their own performance continuously, self-correct for identified changes, and function more reliably than previous designs. Figure 30 shows a simplified block diagram of a typical digital infrastructure design for a new reactor.

The digital infrastructure for the new reactor designs offers several advantages over the analog systems in existing nuclear plants. These include:

- Self-checking capabilities and on-line diagnostics
- Improved accuracy
- Fault tolerance
- Low/no drift

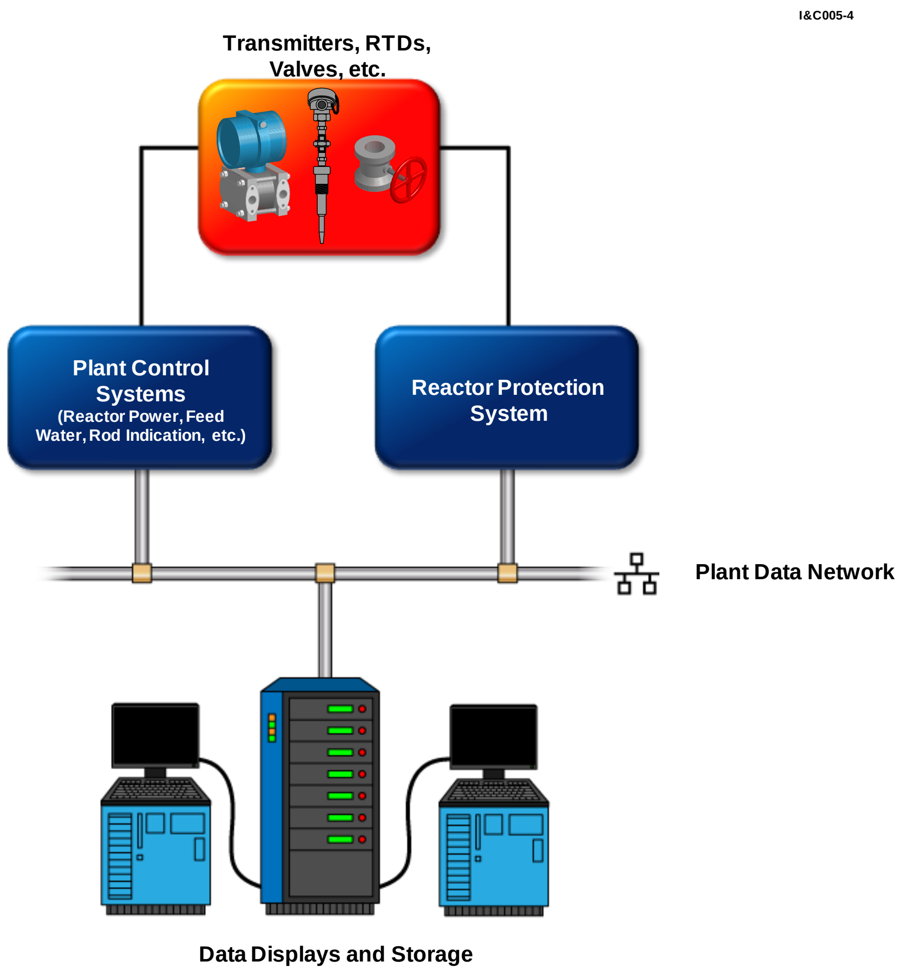


Figure 30: Simplified block diagram of digital infrastructure in new reactor designs

- High data handling and storage capabilities
- Improved human-machine interface

It is important to note that although the infrastructures in new plant designs are digital instead of analog, the sensors envisioned for the new reactor designs will be similar to the types that are used in the existing fleet. For example, resistance temperature detectors (RTDs) and thermocouples will be used to measure primary coolant and core-exit temperatures in the new designs, while conventional pressure transmitters will be used to measure pressures, levels, and flows. As such, the periodic verification and maintenance requirements for these sensors will likely be similar to those in existing plants [Jarrett, Hashemian and Shumaker, 2008]. If this is indeed the case, then the requirements for implementing on-line monitoring (OLM) in the next generation of nuclear power plants will follow those for the existing fleet that were outlined in Section 4 of this paper.

For new plants, however, the instrumentation and control (I&C) infrastructure design is believed to be open, and opportunities therefore still exist to engineer specifications into the initial design to reap the benefits of OLM technologies and avoid future retrofits. This section provides several I&C design recommendations that could help the next generation of nuclear power plants more readily benefit from OLM technologies.

As successful OLM implementations begin with the plant's ability to acquire the proper data, the recommendations outlined in this section focus on improving the data access and retrieval capabilities of the next generation of plants as compared to the existing fleet, including considerations for:

- Increased availability of process sensor data in the plant computer
- Higher sampling frequency and resolution data acquisition capabilities
- Increased redundancy for critical process sensors
- More flexible infrastructure to accommodate future data acquisition needs

Embedding these capabilities in the design will provide an important part of the foundation for improving plant health and condition assessment through OLM in the next generation of nuclear power plants.

5.1 Availability and access to plant sensor data

To use OLM technologies to their fullest extent, plant personnel must first have access to the sensor data. The plant computer provides a central repository for sensor measurements, and as such, should be used as the primary source for OLM data.

As previously indicated in this paper, existing nuclear power plants store most of the sensor measurements needed for OLM analysis in the plant computer; however, some sensors that could benefit from OLM are not sent to the plant computer. For example, most Westinghouse PWRs incorporate dual-element RTDs to measure reactor coolant temperature. These RTDs are required to be cross-calibrated periodically, but normally the spare elements are not connected to the plant computer. As such, the cross-calibration of RTDs must be performed by manually connecting resistance measurement devices to both the active and spare RTDs in order to obtain cross-calibration results. If the spare RTDs were sent to the plant computer, then cross-calibration could be accomplished using data from the plant computer, eliminating the need for dedicated measurement equipment, and saving the plant critical path time at startup.

As a general rule, initial design criteria should provide access to all plant measurements from the plant computer. This has not been done in existing plants primarily because of the costs associated with:

- Installing instrumentation and wiring to bring the measurements to the plant computer

- Storage of the additional data

The costs associated with installing additional instrumentation and wiring may still be relatively high today, but the benefits of providing these to the plant computer for OLM purposes should be weighed against the initial costs. If the additional wiring presents significant design difficulties, implementing wireless capabilities may be an option. An example of a wireless infrastructure that was recently implemented in an existing U.S. nuclear power plant is discussed later in this chapter.

The widespread availability of inexpensive, high-capacity data storage devices today should make additional data storage costs a non-factor in initial plant cost considerations.

5.2 Data acquisition

Not only are OLM technologies dependent on the availability of sensor measurements, they are also dependent on the frequency of the data acquisition and the resolution of the acquired data. If designs of the next generation nuclear power plants are built around using the same types of sensor measurements as the existing fleet of nuclear power plants, the data acquisition requirements for using them with OLM technologies will be similar to existing plants. For static OLM analysis, plants will need sampling periods of 1 – 60 seconds in order to provide OLM algorithms the best possible data. For dynamic OLM analysis, a minimum sample rate of 1 kHz will be required for most of the safety-critical process sensors. Table 9 lists the minimum sample rate requirements for the static and dynamic OLM applications discussed in this paper.

It is anticipated that the new plant designs will incorporate more precise analog-to-digital (A/D) converters than are currently being used in the existing plants. These new A/D converters will likely be 16-bit or 24-bit providing measurements into the microvolt range. This better signal resolution combined with the higher frequency sample rates will allow dynamic OLM technologies to be utilized without supplemental data acquisition equipment. However, to obtain good data at higher frequencies (1 kHz) and low signal levels, an anti-aliasing low-pass filter should be included before the A/D

Table 9: Minimum sample rate requirements for OLM Techniques

Static OLM Application	Sampling Period	Dynamic OLM Application	Sample Rate
Calibration Monitoring (Steady-State)	10 sec.	Dynamic Response	1 kHz
Calibration Monitoring (Startup, Shutdown, Outage)	1 sec.	Reactor Internals	100 Hz
Cross-Calibration	1 sec.	Core Flow Anomaly Detection	1 kHz
Equipment Condition Assessment	60 sec.	Neutron Detector Life Extension	1 kHz

in the instrumentation channel. Without this anti-alias filter, electrical noise that is present will be aliased into the signals and may mask the higher frequency dynamic response information.

Also, as higher frequency data is obtained, it is important that the data from various channels are acquired simultaneously to allow inter-comparisons and cross-correlations to be performed on the data for reactor internals and core flow anomaly detection.

5.3 Plant computer data access

Both static and dynamic sensor data should be available from the plant computer and/or data historian in the next generation of nuclear power plants. In the existing fleet of nuclear power plants, only static OLM data is available from the plant computer due to the limited sampling rate capabilities (< 1 Hz). However, if increased sampling rates up to 1 kHz are realized in the new plant designs, dynamic OLM applications will become much easier to implement.

The vast amounts of data associated with sampling rates in the 1 kHz range, however, may cause the storage of dynamic OLM data to be impractical.

As illustrated in Figure 31, a raw data buffer that provides access to digital sensor data from the plant computer before it is compressed or stored in the data historian may provide an adequate solution for retrieving dynamic OLM data without the need for long-term storage.

A few of the existing plants have obtained a raw data buffer that maintains data for the last 30 days. This is mainly utilized in existing plants to look back for precursors in the data before a plant event or plant trip occurs to help troubleshoot and isolate the problem. However, it has also been extremely beneficial for OLM applications by providing uncompressed data for analysis.

5.4 Redundant sensors for OLM

Averaging methods have been used with great success in existing plants for static OLM applications such as cross-calibration and transmitter calibration monitoring for many years. Averaging algorithms are particularly advantageous for static OLM applications as they are relatively easy to implement, simple to explain, and provide a straightforward means for calculating uncertainties. However, for averaging methods to be successful for OLM, the plant must have a sufficient number of redundant sensors.

For cross-calibration, the number of redundant RTDs is not an issue, as most plants have around 20 to 30 RTDs that can be averaged at isothermal conditions. However, applications such as transmitter calibration monitoring could benefit with the inclusion of more redundant transmitters.

In a typical U.S. plant, most services that would benefit from calibration extension are at best 4-way redundant. The majority of services, however, are 3-way or 2-way redundant. Some services, in fact, have no redundancy. Table 10 lists the number of redundant sensors for services in a typical 3-loop PWR that would benefit from calibration monitoring.

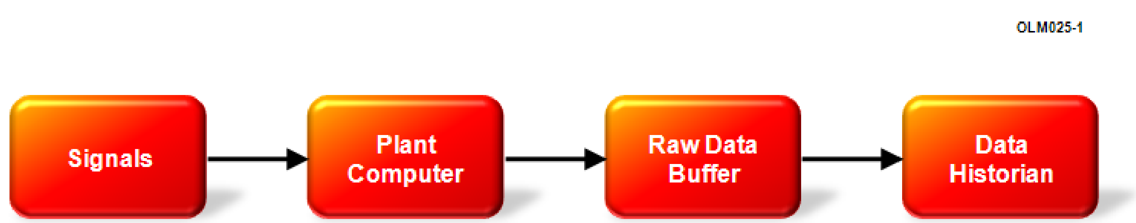


Figure 31: Illustration of sensor data flow

Table 10: Services that would benefit from calibration extension in a typical 3-loop PWR

Service	Redundancy
Reactor Coolant System Loop A Flow	3
Reactor Coolant System Loop B Flow	3
Reactor Coolant System Loop C Flow	3
Pressurizer Level	3
Steam Generator A Narrow Range Level	3
Steam Generator B Narrow Range Level	3
Steam Generator C Narrow Range Level	3
Pressurizer Pressure	3
Steam Generator A Outlet Pressure	3
Steam Generator B Outlet Pressure	3
Steam Generator C Outlet Pressure	3
Containment Pressure	3
Steam Generator A Steam Flow	2
Steam Generator B Steam Flow	2
Steam Generator C Steam Flow	2
Feedwater Flow To Steam Generator A	2
Feedwater Flow To Steam Generator B	2
Feedwater Flow To Steam Generator C	2
Refueling Water Storage Tank Level	2
Turbine First Stage Pressure	2

Although 3-way and even 2-way redundancy is sufficient for calibration extension, 4-way redundancy would be much better from an OLM standpoint. This is due to the reduction of uncertainty of the process estimate and a reduction in the effect of spillover as more sensors are included in the average. Figure 32 illustrates how the uncertainty of the process estimate is reduced as the number of redundant sensors is increased. In this figure, the uncertainty of an individual transmitter is assumed to be 1% of span.

As shown in Figure 32, the process estimate uncertainty is reduced to half of the individual sensor uncertainty (0.5%), when 4 redundant sensors are used in the average. A reduction in process estimate uncertainty should result in more accurate results in applications such as calibration monitoring.

As mentioned before, spillover can distort the results of calibration monitoring by including a drifting sensor measurement in the average. However, as Figure 33 illustrates, the spillover error can be reduced by adding more redundant sensors to the calculation of the process estimate.

As shown in Figure 33, a transmitter that has drifted 1% of span will result in an error of up to 0.5% of span if only two redundant sensors are used to calculate the process estimate. However, as more sensors are included in the average, the effect of a drifting transmitter is significantly reduced.

The main drawbacks to including more redundancy in the design of new nuclear power plants are the increased costs of installing and maintaining additional transmitters. However, the benefits provided by OLM applications that can effectively utilize the increase in redundancy may provide an important justification for these initial costs over the life of the plant.

5.5 Wireless infrastructure

Nuclear power plants have found it difficult and costly to add instrumentation to critical equipment using their existing infrastructures. As a result, measurements on parameters that could provide diagnostics to critical plant processes and equipment are not economically feasible to implement. Much of the cost of adding new instrumentation to existing equipment is in the cabling. In fact, a recent project funded in part by EPRI concluded that adding cabling in existing nuclear plants costs approximately $2000/ft. [EPRI, 2005]. As such, an infrastructure that can accommodate additional instrumentation in the next generation of nuclear plants should be considered in the initial design stages.

Including wireless communication capabilities based on a standard protocol such as 802.11 or ISA 100 Standard in the design plans of the next generation of nuclear power plants can not only provide the necessary means to transmit much needed sensor data, it can also provide an infrastructure for plant-wide communications. The Comanche Peak nuclear plant in Texas has recently provided an example of how beneficial a plant-wide wireless infrastructure can be for OLM technologies [EPRI, 2005]. At Comanche

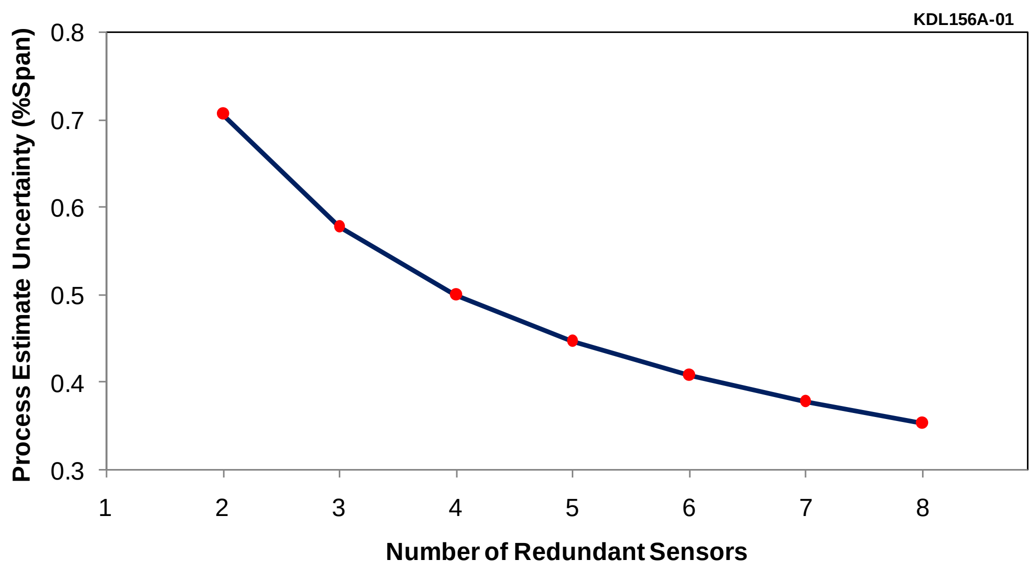


Figure 32: Process estimate uncertainty versus redundancy

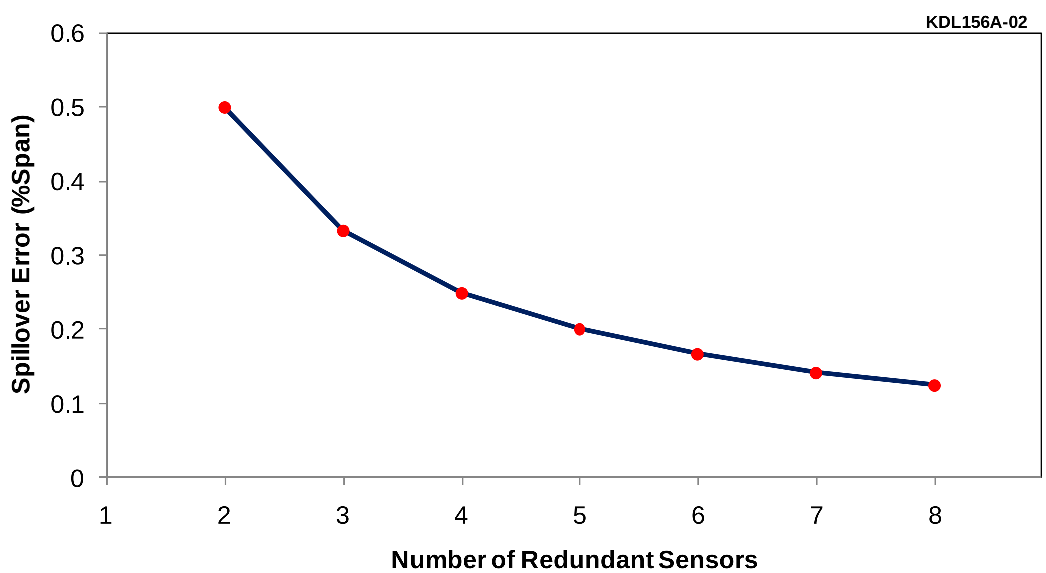


Figure 33: Spillover error versus redundancy

Peak, a wireless infrastructure has been put in place that provides 100% communications coverage throughout the site and gives the plant the ability to add wireless sensors to monitor and analyze various plant processes and equipment.

In the new plants, while the wireless infrastructure should be implemented around an accepted standard, the plant EMI/RFI design should allow for other wireless sensor networks to be deployed side-by-side for various applications. This will allow the wireless sensors from various manufactures to be used for OLM applications in the plants. An example of multiple sensor networks interfacing into the plant data network is shown in Figure 34.

Inevitably, research in OLM methods will continue in the future, and there will be a need to measure and analyze parameters that are not being considered now. Incorporating a wireless infrastructure will help new plants to provide the necessary means of communicating these measurements to plant engineers at a low cost to the plant, and provide a means for the future expansion of OLM capabilities.

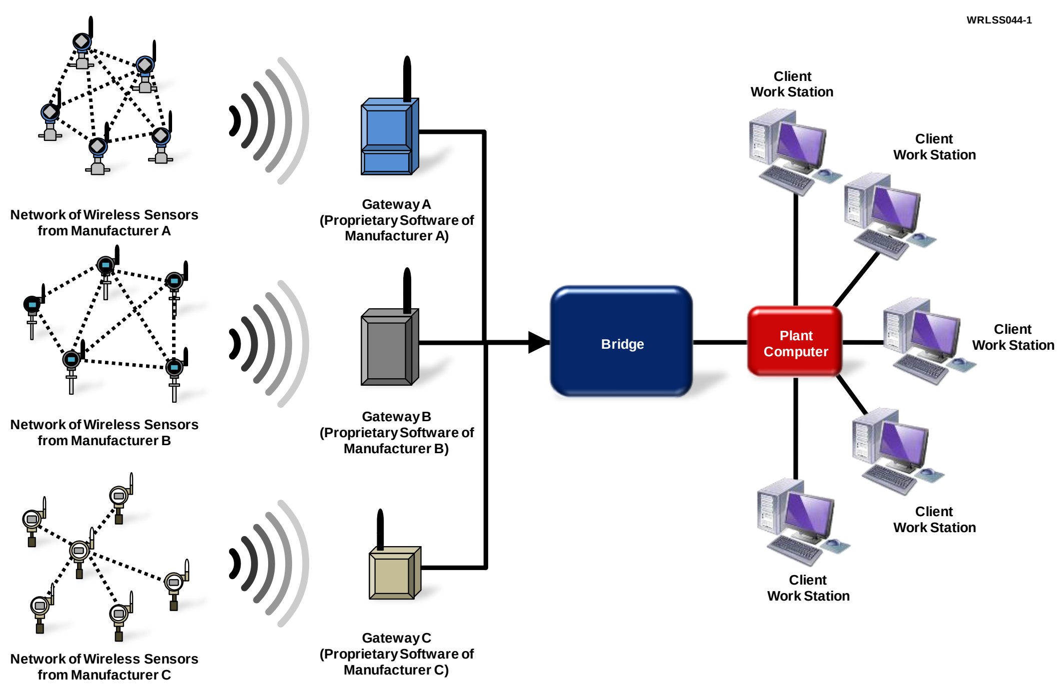


Figure 34: Example of wireless sensors interfaced to the plant data network

5.6 Cyber security

Security of plant systems and data is an issue for both existing plants and the next generation of plants. However, the digital I&C systems that are planned for the next generation of plants are more susceptible to cyber security issues than their analog counterparts in the existing fleet. A significant amount of work has been done in recent years in preparation for this likely increase in cyber security risks.

There are several standards related to cyber security that are available for the electrical power industry including [Kropp, 2008]:

- IEC Security Standards ISO/IEC 27000 series consisting of seven standards
- IEEE P1711 and IEEE P1689 for Cyber Security of Serial SCADA Links
- ISA99 Security for Industrial and Automation Control Systems
- North American Electric Reliability Corporation (NERC) Critical Infrastructure Protection (CIP) standards CIP-002 through CIP-009.

While these standards address different aspects of cyber security for nuclear plants, they focus on many of the same cyber security threats that include:

- Non-directed, damaging attacks by software viruses and worms
- Data network performance attacks from denial of service attacks and network spoofing
- Loss of data privacy and confidentiality from eavesdropping and network packet sniffing
- Directed threats involving network packet modification, mimicking, and data tampering

These cyber threats are traditionally handled by corporate IT departments. However, the impact on plant control systems and plant safety must be evaluated and addressed for new plants with many more plant data networks, digital control, and digital safety systems. While many of these issues will be resolved for the new plant operation, these issues must also be addressed for OLM data systems that will be used to monitor the static and dynamic performance of the plant sensors and systems. The security and configuration of the OLM system is important if this is to be used for meeting safety related technical specifications [Staggs, 2008].

References

Electric Power Research Institute. (2004a). *Equipment condition assessment: Volume 1: Application of on-line monitoring technology*. EPRI, Palo Alto, CA: 1003695.

Electric Power Research Institute. (2004b). *On-line monitoring of instrument channel performance Volume 1: Guidelines for model development and implementation*, EPRI, Palo Alto, CA: 1003361.

Hashemian, H.M. (1995). *On-line testing of calibration of process instrumentation channels in nuclear power plants*. U.S. Nuclear Regulatory Commission, NUREG/CR-6343.

Hashemian, H.M., et al. (1998). *Advanced instrumentation and maintenance technologies for nuclear power plants*. U.S. Nuclear Regulatory Commission, NUREG/CR-5501.

Hines, J.W., and Seibert, R. (2006). *Technical review of on-line monitoring techniques for performance assessment – Volume 1: State-of-the-art*. U.S. Nuclear Regulatory Commission, NUREG/CR-6895.

Electric Power Research Institute. (2006a). *Plant application of on-line monitoring for calibration interval extension of safety-related instruments: Volume* 1. EPRI, Palo Alto, CA, and British Energy Group PLC, Suffolk, UK: 2006. 1013486.

Electric Power Research Institute. (2006b). *Fleetwide monitoring for equipment condition assessment.* EPRI, Palo Alto, CA: 1013589.

Hashemian, H.M. (2007). O*n-line monitoring of accuracy and reliability of instrumentation and health of nuclear power plants: Phase I final report*. U.S. Department of Energy, Washington, D.C.: 2007.

Jarrett, R.A., Hashemian, H.M., and Shumaker, B.D. (2008). *Integrating on-line performance monitoring in new nuclear reactor designs*. 18th Annual Joint POWID/EPRI Controls and Instrumentation Conference & 51st ISA POWID Symposia, Scottsdale, Arizona.

Electric Power Research Institute. (2005a). *Automation in power plants and wireless technology assessments*. EPRI, Palo Alto, CA: 1010468.

Electric Power Research Institute. (2005b). *Demonstration of wireless technology for equipment condition assessment: Application at TXU Comanche Peak steam electric station*. EPRI, Palo Alto, CA: 1011826.

Kropp, T. (2008). *Cyber security - Are we progressing rapidly enough*. 18th Annual Joint POWID/EPRI Controls and Instrumentation Conference and 51st ISA POWID Symposia, Scottsdale, Arizona.

Staggs, K. (2008). *Security solutions to meet NERC-CIP requirements*. 18th Annual Joint POWID/EPRI Controls and Instrumentation Conference and 51st ISA POWID Symposia, Scottsdale, Arizona, USA.

APPENDIX B

Redundant Sensor Averaging Methods for On-Line Monitoring

Redundant Sensor Averaging Methods for On-Line Monitoring

B.1 Averaging Methods

For the on-line calibration monitoring of pressure transmitters, four averaging methods are discussed in this Appendix: straight average, band average, weighed average, and parity space. These methods will each be examined below.

B.1.1 Straight Average

A straight average is just a simple statistical mean of a group of numbers.

Let n be the number of redundant signals.

Let a measurement of each redundant signal be represented by:

$$X_1 + X_2 + ... + X_n \tag{B.1}$$

The straight average or mean of a set of measurements is:

$$\mu = \frac{X_1 + X_2 + ... + X_n}{n} \tag{B.2}$$

This is just the sum of the redundant signals divided by the number of redundant signals. This is the simplest method and weights all the redundant signals equally.

B.1.2 Band Average

The band average method places a limit around the straight average. If a measurement exceeds the limit around the straight average, then it is removed from the signals being averaged and the straight average is recalculated. This process is repeated until all the remaining signals fall within the limit around the straight average.

$$\text{Band Average} = \sum_{i=1}^{n} \begin{pmatrix} X_i, (|X_i - \mu| \leq BandLimit) \\ 0, (|X_i - \mu| > BandLimit) \end{pmatrix} \Bigg/ \begin{matrix} \text{number of remaining} \\ \text{measurements} \end{matrix} \qquad \text{(B.3)}$$

or

$$\text{Straight Average with } \left[|X_i - \mu| > \text{limits}\right] \text{ removed from the measurements} \qquad \text{(B.4)}$$

The selection of the band limit is traditionally selected at the allowable drift limit or slightly smaller so that when signals have drifted outside of their drift allowance, they are no longer included in the average. However, if the signal variance is large, the band may need to be larger than the drift allowance so the average is not skewed by instantaneous signal fluctuations. These limits will be determined after evaluating the historical plant computer data.

B.1.3 Weighted Average

The weighted average, as the name implies, weights the measurements based on either a predetermined factor such as narrow range and wide range signals that have different accuracies, or a calculation performed for each set of measurements such as a measurement's deviation from the straight average. The weighted average formula is simply:

$$\text{Weighted Average} = \frac{W_1 X_1 + W_2 X_2 + ... + W_n X_n}{W_1 + W_2 + ... + W_n}, \text{ all } W \geq 0 \qquad \text{(B.5)}$$

Each measurement is multiplied by a weighting factor and all the results are summed. This sum is then divided by a sum of all the weighting factors. The other two methods of a straight average and a band average may be expressed in terms of a weighted average:

If all $W_i = 1$, then weighted average = straight average

When all the weights equal one, the sum of the n weights equal n and the equation reduces to the straight average.

$$\text{if } \begin{pmatrix} W_i = 1, \left(\left| X_i - \mu \right| \le \text{limit} \right) \\ W_i = 0, \left(\left| X_i - \mu \right| > \text{limit} \right) \end{pmatrix} = \text{Band Limit} \tag{B.6}$$

The weights are equal to one when the measurement is inside the band limit and equal to zero when the measurement is outside the band limit. When the weights are selected this way, the weighted average reduces to the band average equation.

There are many different types of weighted averages. For this project, one may be selected that is easy to implement, or that has a simple uncertainty calculation. The uncertainty will be discussed in the next section.

B.1.4 Parity Space

The parity space method may be expressed as a weighted average. The parity space method sets the weights based on the number of points around a particular measurement that fall within a band. Each redundant measurement is compared against every other redundant measurement to see if it falls within a parity space limit. For every measurement within the limit, the weight being calculated is increased by 1. Once all the weights are determined, the weighted average is calculated. This weight calculation can be expressed as:

$$W_i = \sum_{j \ne i}^{n} \begin{pmatrix} 0, \left(\left| X_j - X_i \right| > \text{limit} \right) \\ 1, \left(\left| X_j - X_i \right| \le \text{limit} \right) \end{pmatrix}, \text{ for } i = 1 \text{ to } n \tag{B.7}$$

For the parity space method, selecting the limit has a large contribution on the effectiveness of this method. If the limit is selected very large, then all the measurements have the same weight and this reduces to the straight average. If the limit is smaller than the deviation between the measurements, then some measurements will have a weight of zero and the remaining measurements may have the same weight. This would reduce the parity space method to the band average. When the limits are selected so that all the measurements are within the limit of at least one other measurement, then a true weighted average results. This will weight the measurements that are the closest togther more than measurements that fall away from the majority.

Although this is the most complicated of the methods discussed, it has the advantage of producing a smooth average estimate as a sensor drifts away. For the band limit, when a sensor drifts beyond the limit, the average will suddenly jump to the average of the remaining signals which will create a sudden large deviation of the outlying signal. The parity space method will create a gradual decreasing weight as it moves away from the majority of the other measurements. In this case, its deviation will be evident earlier and not be a sudden jump away from the others.

B.2 Uncertainty of the Weighted Average

Since the weighted average can describe all the averaging methods, once its uncertainty is determined, all others can be easily calculated. The general formula for uncertainty with bias may be expressed as the root sum square (RSS) of the individual uncertainties in an equation multiplied by the partial derivative of the equation with respect to each individual variable. This can be expressed as:

$$\sigma_t = \pm\sqrt{\left(\frac{\partial}{\partial X_1}\sigma_1\right)^2 + \ldots + \left(\frac{\partial}{\partial X_n}\sigma_n\right)^2} \qquad \text{(B.8)}$$

To calculate the total uncertainty for the weighted average, first we should calculate the partial derivative with respect to each variable. For example the partial with respect to the first variable, X1, is:

$$\partial^{(WA)}\!\big/\partial X_1 = \partial\!\big/\partial X\left(\frac{W_1 X_1 + W_2 X_2 + \ldots + W_n X_n}{W_1 + W_2 + \ldots + W_n}\right) = \frac{W_1}{W_1 + W_2 + \ldots + W_n} \qquad \text{(B.9)}$$

or this can be written for each variable as:

$$\partial \big/ \partial X_i = \frac{W_i}{W_1 + W_2 + \ldots + W_n} \tag{B.10}$$

So, if we replace these partial derivative calculations into the original equation we obtain:

$$\sigma_t = \frac{\sqrt{(W_1\sigma_1)^2 + (W_2\sigma_2)^2 + \ldots + (W_n\sigma_n)^2}}{W_1 + W_2 + \ldots + W_n} \tag{B.11}$$

For the other averaging techniques, their uncertainties may be calculated:

For simple average: $$W_i = 1, \quad \sigma_t = \frac{\sqrt{\sigma_1^2 + \sigma_2^2 + \ldots + \sigma_n^2}}{n} \tag{B.12}$$

Here the simple average is just the RSS of the individual uncertainties divided by n.

$$\text{if } \sigma_i = \sigma, \; \sigma_t = \frac{\sigma}{\sqrt{n}} \tag{B.13}$$

when the individual uncertainties are all the same for the straight average, the total reduces to the individual uncertainty divided by the square root of the number of measurements.

For weighted average, $$\text{if } \sigma_i = \sigma, \sigma_t = \sigma \frac{\sqrt{W_1^2 + W_2^2 + \ldots + W_n^2}}{W_1 + W_2 + \ldots + W_n} \tag{B.14}$$

when the individual uncertainties are the same for the weighted average, the total uncertainty becomes the individual uncertainty multiplied by the RSS of the weights divided by the sum of the weights.

From this equation it can be seen that if the weights are predetermined, then the uncertainty of the method can also be predetermined. However, if the weights are calculated based on the measurements such as in band average or parity space method, then the uncertainty of the method will be different with each set of measurements. To quantify the measurement uncertainty in these cases, the total uncertainty may be expressed by either an average of the calculated measurement uncertainties or just the maximum uncertainty obtained for a set of data.

APPENDIX C

Kernel Regression Theory

Kernel Regression Theory

Kernel regression is a memory-based technique that predicts noise-free estimates of the given input signals based on a weighted average of stored training data. Kernel regression is often referred to in the literature as a 'lazy-learning' technique because it defers learning the relationships between input variables until it receives a test data sample, also known as a query [1]. Lazy-learning techniques are in sharp contrast to other types of algorithms, such as neural networks, that attempt to establish the global relationships between variables during training. Techniques like neural networks can suffer from very long training times and give unpredictable results if the global relationships between the variables change over time. Kernel regression is more robust than neural networks in this respect because it only tries to approximate the relationships between the variables *locally*, and does not try to approximate global relationships [2].

Kernel regression stores its fault-free training data in an N-by-P memory matrix **M**, which is made up of N observations of P process variables:

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \dots & m_{1,P} \\ m_{2,1} & m_{2,2} & \dots & m_{2,P} \\ \dots & \dots & \dots & \dots \\ m_{N,1} & m_{N,2} & \dots & m_{N,P} \end{bmatrix} \tag{C.1}$$

For each query vector $q_i = [q_1 \quad q_2 \quad \dots \quad q_P]$ presented to the kernel regression model, the distance between q_i and each vector in the memory matrix **M** is calculated according to a distance function, such as the Euclidean distance given by:

$$d_i(M, q_i) = \sqrt{(M_{i,1} - q_1)^2 + \dots + (M_{i,p} - q_p)^2} \tag{C.2}$$

For each input vector q_i, the calculation in (C.2) results in a vector $d_i = [d_1 \quad d_2 \quad \dots \quad d_N]$ made up of the distances between the query vector, q_i, and all of the vectors in the memory matrix **M**. Next, these distances are used to calculate a weighting vector w_i according to a similarity function, typically given by the Gaussian kernel function:

$$w_i = K_k(d_i) = e^{-d^2/k^2} \tag{C.3}$$

where K_k is a kernel function, and k is the kernel width. The kernel function effectively gives higher weights to memory matrix vectors that are closer to the query vector q_i. Finally, these weights are used to produce the output prediction, $\hat{y}_i$, according to:

$$\hat{y}_i = \frac{\sum_{i=1}^{N} w_i M_i}{\sum_{i=1}^{N} w_i} \tag{C.4}$$

where the output prediction $\hat{y}_i$ is a weighted average of memory vectors in **M**.

Figure C-1 shows eleven sample training points of a one-dimensional data set generated from the equation:

$$y_i = 2x_i - \frac{1}{50}x_i^2 \tag{C.5}$$

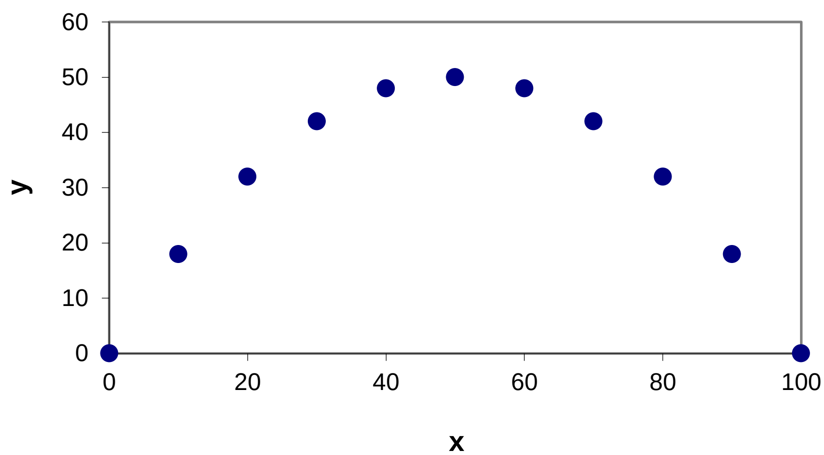


Figure C-1
One-Dimensional Training Data Set

The table to the right of Figure C-1 shows the corresponding *x* and *y* values for each of the eleven training points. The eleven *x* and *y* training value pairs are all that kernel regression model 'knows' about the data set. The kernel regression model does not attempt to discover the *global* mathematical relationship between *x* and *y*, as described in Equation 5, rather it calculates estimates for new data on a point-by-point basis.

For example, suppose the model from Figure C-1 is presented with a query value that is not in the training data, such as $x = 15$. To calculate the corresponding y value, the Euclidean distance between $x = 15$ and the eleven *x* values in the training data are calculated. The distances are then converted to weighting factors using a kernel function. Finally, the weighting factors are used to weight the eleven corresponding *y* values in the training set to produce the estimate. Figure C-2 shows the kernel regression model estimate for $x = 15$, using the Euclidean distance measure and a Gaussian kernel function with a kernel width of 0.3.

Figure C-2 shows that the new *y* estimate for $x = 15$ lies between point 2 and point 3 of the training data. The table to the right of Figure C-2 shows that this is because the y values of training points 2 and 3 have a weight factor of 0.5, and the rest of the training points have a weight factor of 0.0, meaning that the new estimate is simply the average of training points 2 and 3. Note that the weight factors of all of the training samples are calculated, but the training points that are closest to the query point have the most influence on the final estimate.

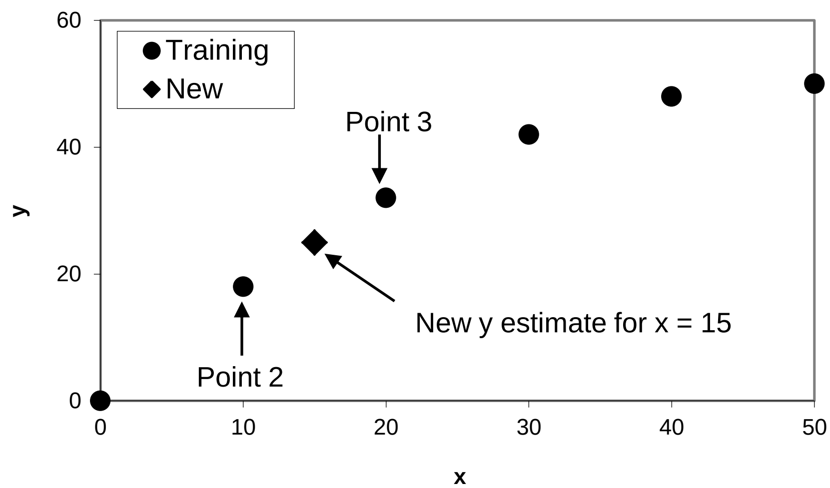


Figure C-2
Kernal Regression Estimate for x = 15

The weight factor given to each estimate is dependent on the distance of the query from the known training points, the kernel function, and the kernel width. Figure C-3 shows the Gaussian kernel function with different values of kernel width.

As shown in Figure C-3, the weight factor decreases as the distance increases, and is dependent on the value of the kernel width parameter k. As the kernel width is increased, the weight factors of more distant points increase, allowing distant points to influence the calculation of the estimate. Figure C-4 shows the estimates from $x = 0$ to $x = 100$ for the example data with a kernel width of 0.3. The estimates for this kernel width value fit the training data, and follow the overall pattern closely.

Figure C-5 shows the estimates using a kernel width of 0.1. The estimates fit the training points well, but do not follow the pattern between training points. In this case, the kernel width is too small to allow multiple training points to influence the estimate when the queries are between training points, and as a result, the model does not interpolate well.

Figure C-6 shows the estimates of the example data using a kernel width of 0.8. In this case, distant points influence the local estimates too much, resulting in biased estimates. In fact, as the kernel width approaches infinity, each estimate approaches the average of all of the training points.

As shown in the example data, the choice of kernel width can have a significant effect on the performance of the model. There are also other parameters in kernel regression models that must be considered in order to produce the most accurate and robust models. These parameters are listed in Table C-1.

Much has been written about these parameters and their influence on the overall effectiveness of kernel regression models, a sample of which can be found in [3-7]. The effects of adjusting these parameters can be quantified by measuring the model output against a variety of modeling metrics, as listed in Table C-2. These metrics give an objective means for comparing and optimizing various kernel regression models.

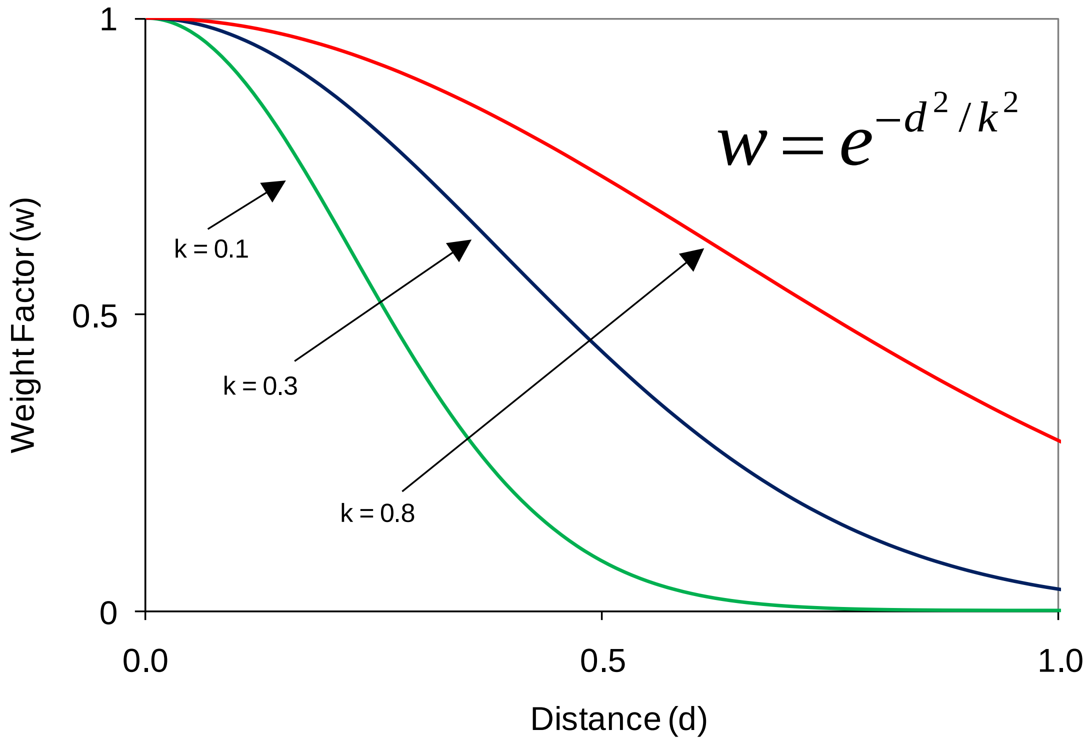


Figure C-3
Gaussian Kernal Function with Different Values of Kernel Width

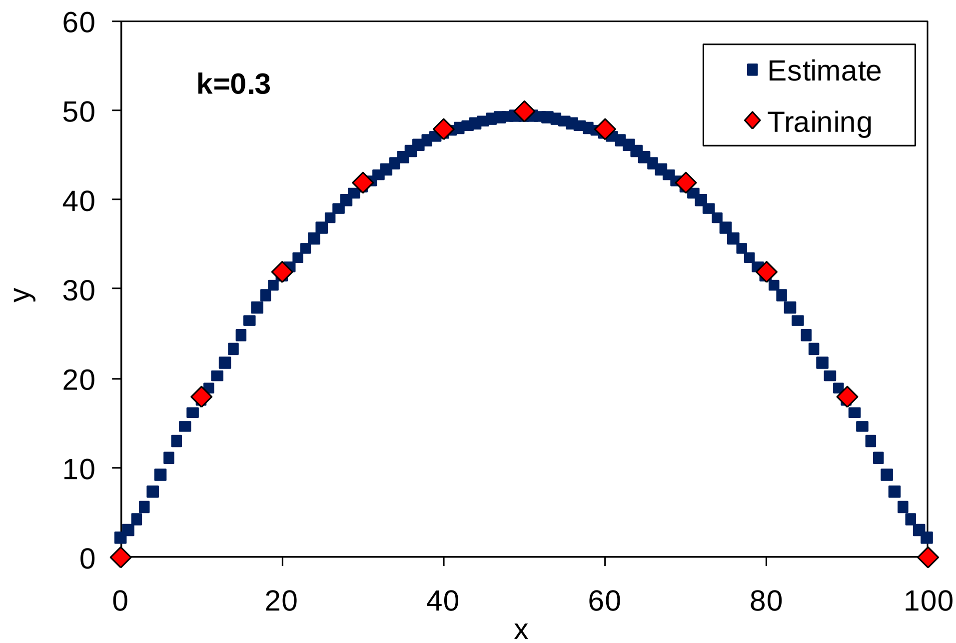


Figure C-4

Estimates using Kernel Width of 0.3

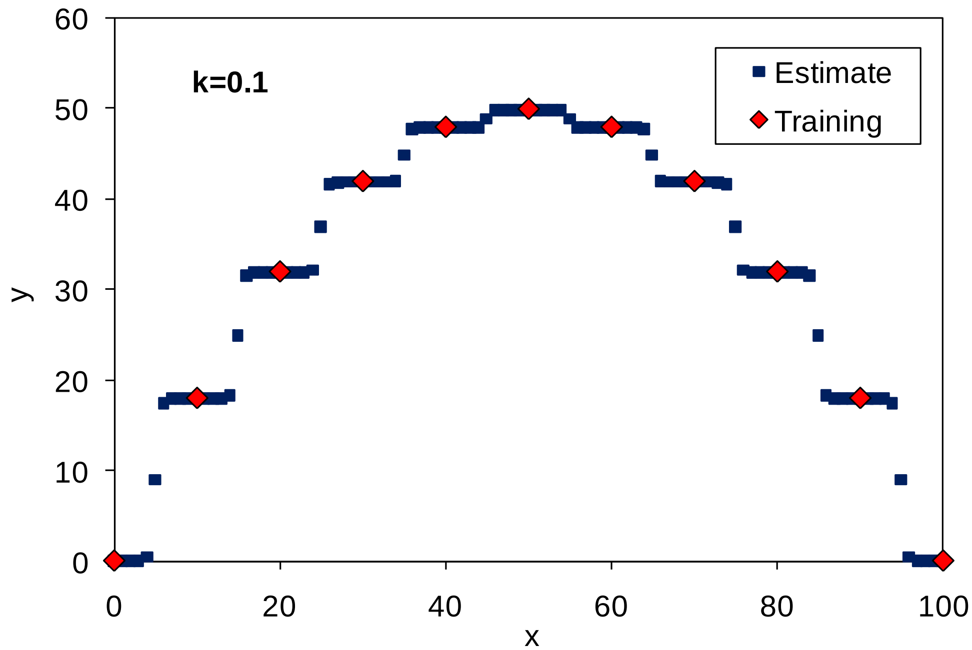


Figure C-5
Estimates using Kernel Width of 0.1

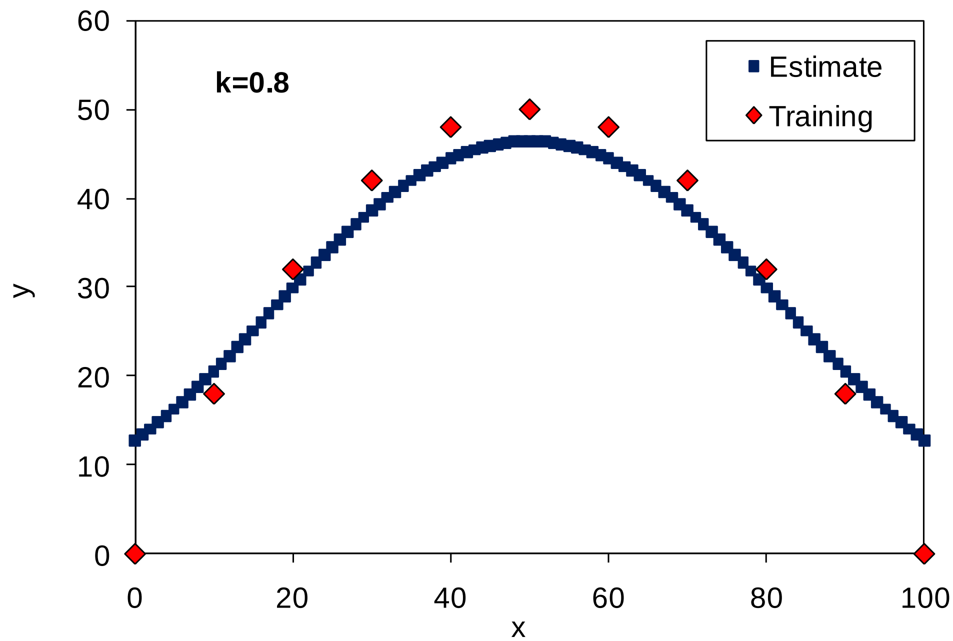


Figure C-6
Estimates using Kernel Width of 0.8

Table C-1
Kernel Regression Parameters

Parameter	Description
Memory Matrix	Representative samples from the training data
Distance Function	The function used to determine the similarity between pairs of vectors
Kernel Function	The function used to calculate the weight factors for the memory matrix vectors
Kernel Width	Parameter of the kernel function used to determine the weight factors

Table C-2
Metrics for Model Comparison

Parameter	Description
Accuracy	Mean-Squared-Error between model predictions and target values
Auto-Sensitivity	Measure of a model's ability to make correct predictions in the presence of a fault condition
Cross-Sensitivity	Measure of the effect a faulty sensor has on other predictions in the same model
Uncertainty	Error-bounds around model predictions
Detectability	Smallest sensor drift that can be identified by the model

Brief descriptions of each of these metrics are given below. For more detailed descriptions of these metrics and their effects on kernel regression models, the reader is referred to the material in [8-12].

Accuracy

A model's accuracy is measured by calculating the cumulative error between the model's predictions and target values. Accuracy is calculated using fault-free training data, and is calculated as a mean-squared error value according to (C-6) (for a one dimensional model):

$$A = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2 \qquad \text{(C.6)}$$

where y_i is the target value, $\hat{y}_i$ is the model prediction, and N is the number of samples. Figure C-7 shows an example of the errors between the model predictions and the target values for a one-dimensional case. All of the individual errors are squared, summed, and then averaged to calculate the accuracy.

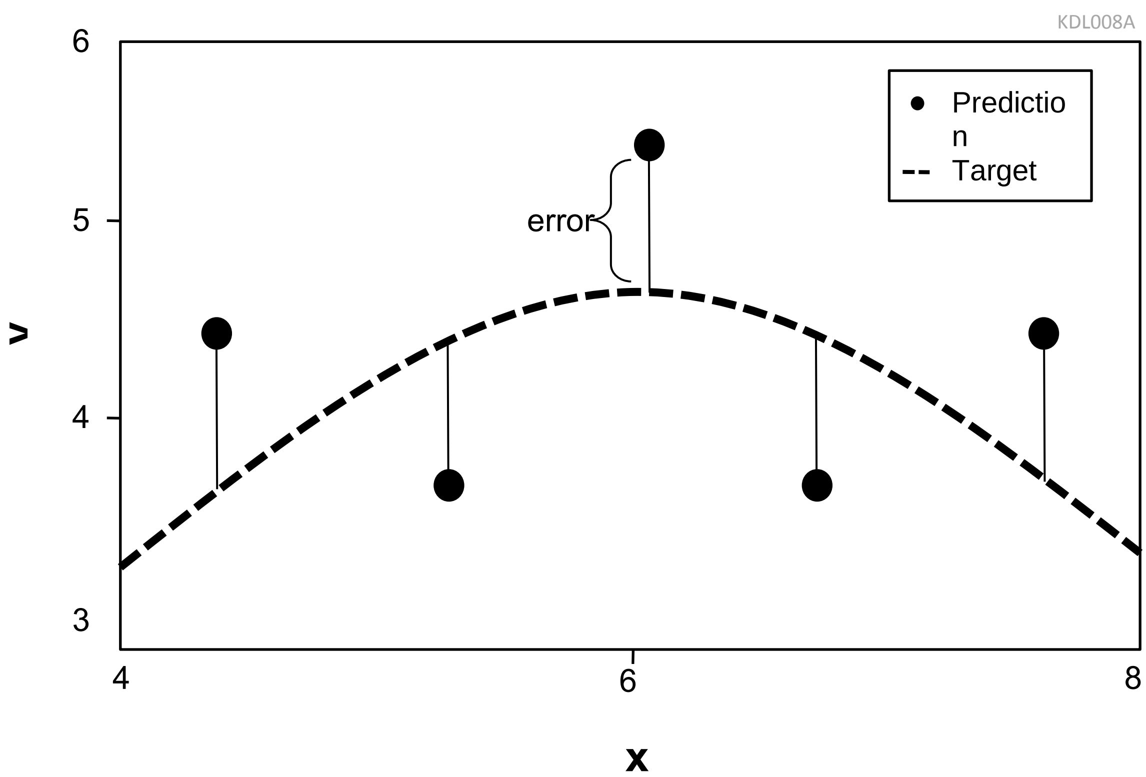


Figure C-7
Errors Between Predictions and Target Values for One-Dimensional Model

The accuracy metric can be used to help choose an appropriate value for the kernel width parameter. In this case, a model is trained with fault-free data, and then tested with another set of fault-free data that is different from the training data. The same test data is applied to the training data as the kernel width is incremented. Then the mean-squared-error versus the kernel width is plotted to reveal a curve similar to the one shown in Figure C-8. The appropriate kernel width could then be chosen as the value that minimizes the mean-squared error.

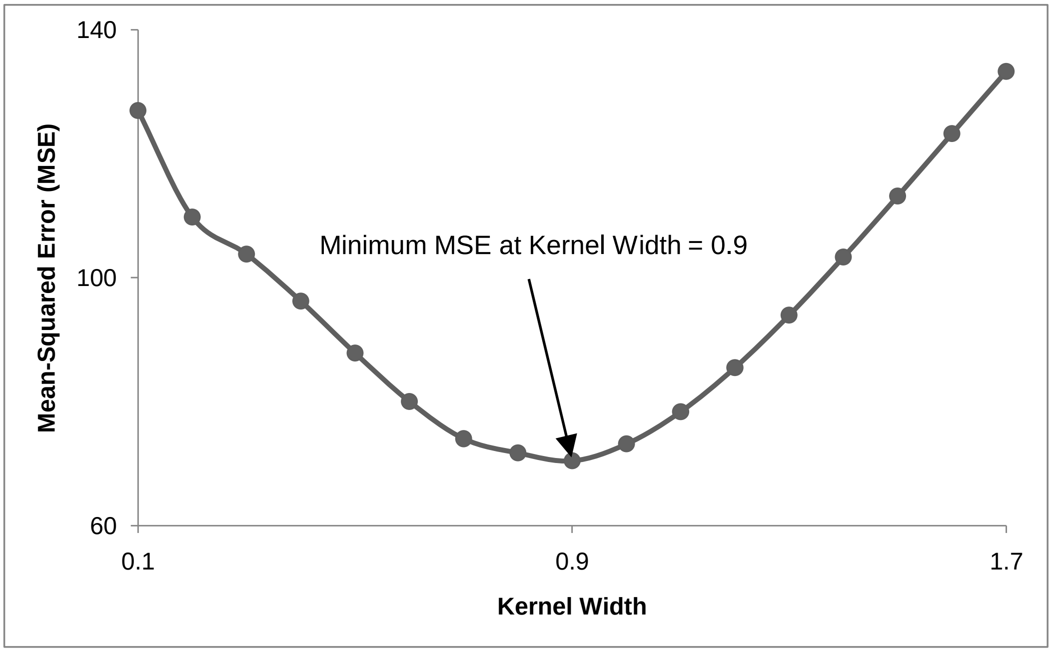


Figure C-8
Mean-Squared-Error Versus Kernel Width Auto-Sensitivity

One of the most important attributes of an empirical model is its ability to make correct predictions in the presence of drifting inputs. This is especially true in applications of on-line calibration monitoring where the detection of drift is of primary concern. In an on-line monitoring application, the difference between the model input and the model output for a given sensor is used to calculate a residual. This residual is then compared against acceptance limits to determine if the sensor has drifted. Ideally, the model output for a sensor would be robust to a drifting input, which would result in a large residual that reflected the fact that the sensor was drifting (Figure C-9). The worst case would be if the model output drifted along with the input, in which case the residual would be small, and the drift may go undetected (Figure C-10).

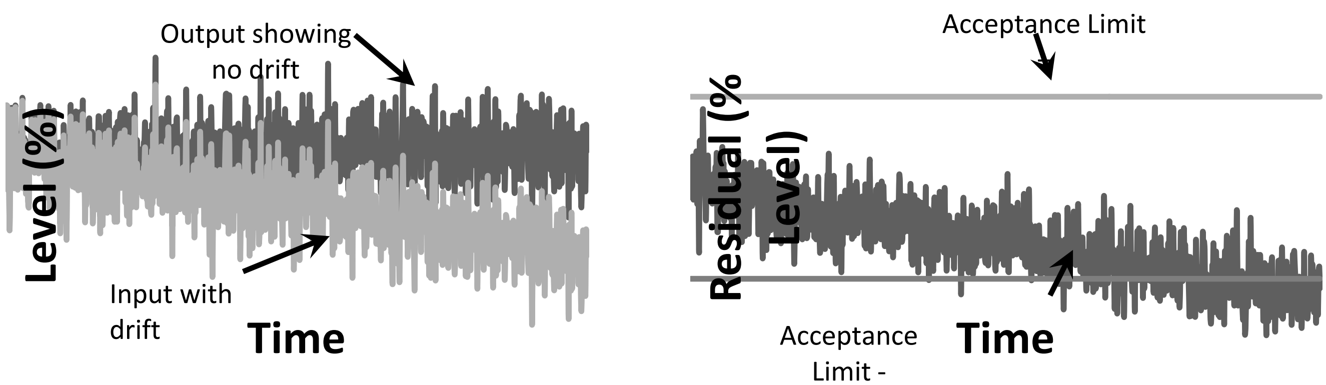


Figure C-9
Output and Residual for Model With Low Auto-sensitivity

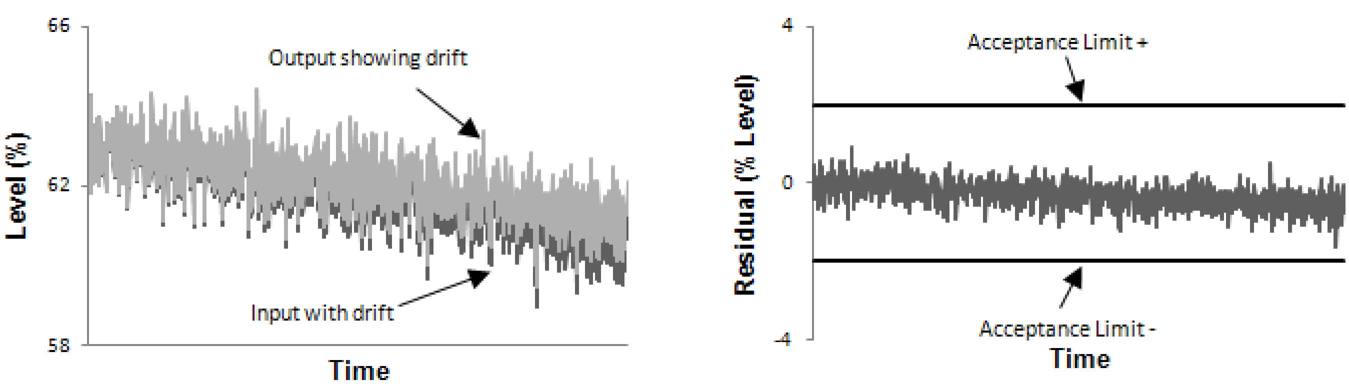


Figure C-10
Output and Residual for Model With High Auto-Sensitivity

Auto-sensitivity is a metric that quantifies robustness to drift of each sensor in a model. It is calculated by artificially drifting a sensor, and then calculating the ratio of the model's output drift with the actual drift introduced. For sensor *i*, the auto-sensitivity is calculated by:

$$S_{A_i} = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{\hat{y}_{ki}^{drift} - \hat{y}_{ki}}{x_{ki}^{drift} - x_{ki}}\right| \tag{C.7}$$

where $\hat{y}_{ki}^{drift}$ is the model output of sample *k* of the drifted sensor *i*, $\hat{y}_{ki}$ is the model output of sample *k* of sensor *i* with no drift applied, x_{ki}^{drift} is sample *k* of the drifted input for sensor *i*, x_{ki} is sample *k* of sensor *i* with no drift applied, and *N* is the number of samples. An auto-sensitivity value of 0 indicates that the sensor model is robust to drift, and a value of 1 indicates that the sensor model will mask drift.

Cross-Sensitivity

Another important model characteristic is the robustness of a sensor prediction in the presence of faults in other sensors in the model. This characteristic is called cross-sensitivity, and is similar to auto-sensitivity. However, the cross-sensitivity for a given sensor is calculated by artificially drifting all of the other sensors in the model, and determining the effect the drift has on the sensor's output. For a sensor *j*, cross-sensitivity is given by:

$$S_{C_{ji}} = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{\hat{y}_{kj}^{drift} - \hat{y}_{kj}}{x_{ki}^{drift} - x_{ki}}\right| \tag{C.8}$$

where $\hat{y}_{kj}^{drift}$ is the model output of sample *k* of the drifted sensor *j*, $\hat{y}_{kj}$ is the model output of sample *k* of sensor *j* with no drift applied, x_{ki}^{drift} is sample *k* of the drifted input for sensor *i*, x_{ki} is sample *k* of sensor *i* with no drift applied, and *N* is the number of samples. A cross-sensitivity value of 0 indicates that the sensor model is robust to the drift of other sensors, and a value of 1 indicates that the sensor model is affected by the drift of other sensors.

Uncertainty

In order for model predictions to be used in applications such as on-line calibration monitoring, an estimate of their uncertainty must be attainable. For on-line calibration monitoring applications, the uncertainty of a model estimate is a contributor to the overall acceptance limits, and thus has a significant effect on the model's ability to detect drift. The following description of kernel regression uncertainty calculations is brief, however the reader is referred to the material in [9][10][12] and [13] for more detailed information.

There are two different types of uncertainty estimations that can be calculated for a kernel regression model, namely *prediction intervals* and *confidence intervals* [10]. Prediction intervals give the uncertainty around each individual prediction, while confidence intervals provide the uncertainty around the residual formed from subtracting the model estimate from the measured value. Figures C-11 and C-12 illustrate the concepts of prediction and confidence intervals respectively.

According to [10], the prediction interval around a given model estimate $\hat{y}$ with a 95% confidence level is given by:

$$\hat{y} \pm 2\sqrt{\sigma_e + Var(\hat{y}) + Bias^2} \qquad \text{(C.9)}$$

where

$Bias^2$	= the systematic error of the model predictions
$Var(\hat{y})$	= the variance of the model predictions
σ_e	= the estimate of the noise variance on $\hat{y}$.

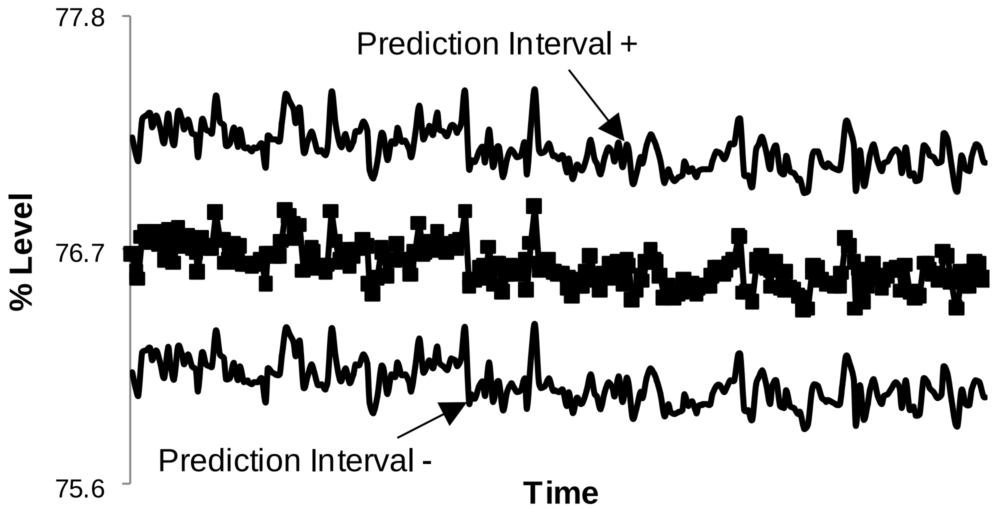


Figure C-11
Predicition Intervals Around Model Predictions

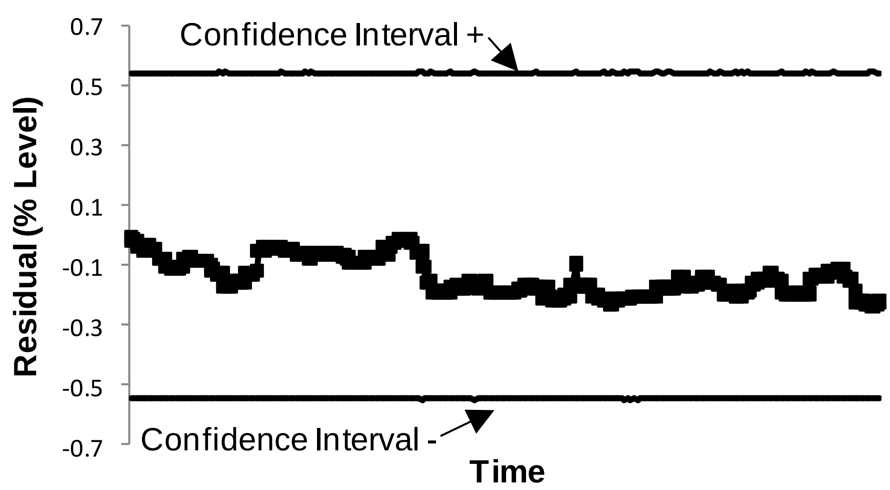


Figure C-12
Confidence Intervals Around Residual

Similarly, the 95% confidence interval around the residual $E(\hat{y})$ is given by:

$$E(\hat{y}) \pm 2\sqrt{Var(\hat{y}) + Bias^2} \tag{C.10}$$

where

$Bias^2$ = the systematic error of the model predictions

$Var(\hat{y})$ = the variance of the model predictions.

Note that the only difference between the prediction and confidence intervals is that the confidence interval does not include the noise variance term σ_e, as this term is assumed to be cancelled out in the calculation of the residual. As a result, confidence intervals are typically much smaller than prediction intervals, making them more feasible for inclusion in acceptance criteria calculations for on-line calibration monitoring applications [10].

The uncertainty intervals for kernel regression models can be calculated analytically or experimentally using Monte Carlo methods. A particular advantage of kernel regression models over other methods such as neural networks is that the use of Monte Carlo techniques to estimate the uncertainty is practical in kernel regression models due to the short training times.

Detectability

For OLM applications, the most important characteristic of an empirical model is its ability to detect drift. Therefore, the model's ability to detect drift must be quantified such that the engineer can determine if the model will be effective. For example, if a certain sensor is allowed to drift only 1% of its range over a given time period, the model must be able to detect drifts of at least 1% of the sensor's range, or the model will be ineffective. The detectability metric quantifies the smallest amount of drift detectable for a given sensor in a model and is given by [8]:

$$D_i = \frac{U_i}{1 - S_{Ai}} \tag{C.11}$$

where U_i is the sensor's 95% confidence interval, and S_{Ai} is the sensor's auto-sensitivity. The detectability D_i is given as a percentage of the sensors total range. Therefore, a D_i of 1% means that the smallest amount of drift that the sensor can detect is 1% of its range. The detectability for each sensor is subtracted from the acceptance limits so that drift can be appropriately detected.

References

1. *Machine Learning*. Mitchell, T., McGraw Hill: 1997.

2. *Locally Weighted Learning*. Atkeson, C.G., Moore, A.W., Schaal, S, Artificial Intelligence Review, Volume 11, Number 1-5, pp. 11-73: 1997.

3. *Similarity Based Methods: A General Framework for Classification, Approximation and Association*. Duch, W., Control and Cybernetics, Volume 29, No. 4: 2000.

4. *Learning From Data*. Cherkassky, V., Mulier, F., John Wiley & Sons, Inc.: 1998.

5. *Reduction Techniques for Instance-Based Learning Algorithms*. Wilson, D.R., Martinez, T.R., Machine Learning, 38-3, pp. 257-286: 2000.

6. *Robust Distance Measures for On-Line Monitoring: Why Use Euclidean?*. Garvey, D.R., Hines, J.W., Proceedings of the 7th International FLINS Conference on Applied Artificial Intelligence Systems for Applied Research, Genova, Italy: August 2006.

7. *Traditional and Robust Vector Selection Methods for use with Similarity Based Models*. Hines, J.W., Garvey, D.R., presented at the American Nuclear Society (ANS) Topical Meeting on Nuclear Power Plant Instrumentation and Control and Human Machine Interface Technologies (NPIC&HMIT), held concurrently with the ANS National Winter Meeting, Albuquerque, New Mexico, USA: November 2006.

8. *Development and Application of Fault Detectability Performance Metrics for Instrument Calibration Verification and Anomaly Detection*. Hines, J.W., Garvey, D.R., Journal of Pattern Recognition Research, 1, 2-15: 2006.

9. *Technical Review of On-Line Monitoring Techniques for Performance Assessment Volume 1: State-of-the-Art*. Hines, J.W., Seibert, R., Arndt, S.A., NUREG/CR-6895, U.S. Nuclear Regulatory Commission: January 2006.

10. *Technical Review of On-Line Monitoring Techniques for Performance Assessment Volume 2: Theoretical Issues*. Hines, J.W., Garvey, D., Seibert, R., Usynin, A., Arndt, S.A., U.S. Nuclear Regulatory Commission: to be published.

11. *Technical Review of On-Line Monitoring Techniques for Performance Assessment Volume 3: Limiting Case Study*. Hines, J.W., Garvey, D., Garvey, J.,Seibert, R., Arndt, S.A., U.S. Nuclear Regulatory Commission: to be published.

12. *Extension of Analytic Prediction Interval Methodologies of Nonparametric Empirical Models from Inferential to Autoassociative Architectures*. Garvey, D.R., Master's Thesis, University of Tennessee at Knoxville: 2005.

13. *Prediction Interval Estimation Techniques for Empirical Modeling Strategies and their Applications to Signal Validation Tasks*. Rasmussen, B.R., Ph.D Dissertation, University of Tennessee at Knoxville: 2003

APPENDIX D

Tutorial on the Noise Analysis Technique

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Tutorial on the Noise Analysis Technique

Noise analysis is the process of extracting information from the normally occurring fluctuations which occur on the output of most sensors while the plant is operating. These fluctuations are usually due to normal structural vibration, flow turbulence, random heat transfer, random flux, and other effects. These fluctuations are referred to as noise, and the processing of this noise is called noise analysis. One of the most familiar applications of noise analysis is monitoring of rotating machinery in industrial processes. In these applications, vibration sensors such as accelerometers are used to provide information about displacement, velocity, or acceleration of the rotating equipment. In nuclear power plants, in addition to vibration sensors, noise signals from temperature, pressure, neutron, and other sensors are used to study the dynamics of the system and provide the frequency response of the sensors themselves.

The noise data is separated from the steady state output of the sensor by a routine signal conditioning procedure such as the one illustrated in Figure D-1. A high-pass filter is used to remove the DC component of the signal so that the noise can be amplified (a DC offset voltage can also be used instead of the high-pass filter). The amplified signal is then sent to a low-pass filter to remove any undesirable high-frequency component of the noise and to provide for anti-aliasing. The filtered signal is then sampled (i.e., digitized by an analog-to-digital or A/D converter) with a computer and stored on a computer disk for subsequent analysis. The sampling rate, amplifier gain, and the high-pass and low-pass filter settings are selected based on the frequency range of interest.

Analysis of Noise Data

The noise data may be analyzed in the amplitude domain, time domain, or frequency domain. For any of these analyses, the mean or average value of the noise signal is usually subtracted out unless the signal has been high-pass filtered, in which case, the mean value is zero. These analyses are described below.

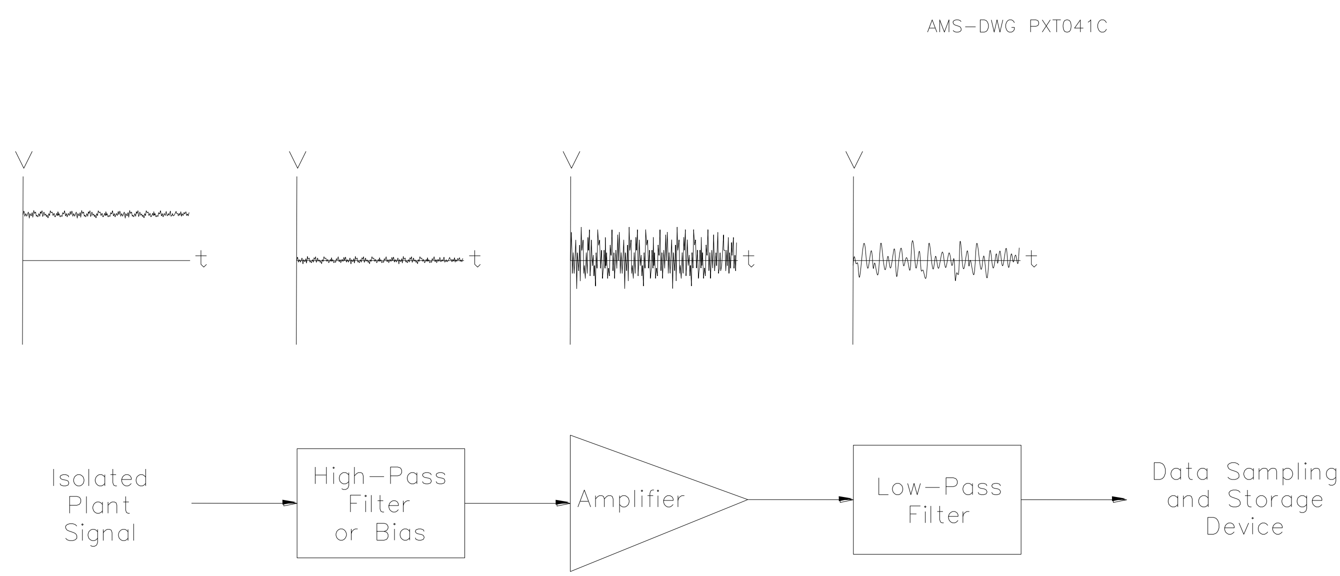

Figure D-1
Block Diagram of Signal Conditioning and Noise Data Acquisition Equipment

Amplitude Domain Analysis

In amplitude analyses, the root mean squared (RMS) value, the variance, and the amplitude distribution of the noise signals are calculated. If the signal is denoted as $x(t)$, then the RMS value is calculated as:

$$RMS = \sqrt{\overline{x^2}} \qquad \text{(D.1)}$$

where the bar is used to represent the average value. In discrete form, Equation (D.1) would be shown as

$$RMS = \sqrt{\sum_{i=1}^{N} \frac{x_i^2}{N}} \qquad \text{(D.2)}$$

where N is the number of points sampled and x_i is an individual sample. The RMS value is also referred to as standard deviation and denoted as σ.

The RMS value of a signal provides a quantitative measure of the magnitude of the variations occurring in the signal. A related quantity called variance is also used. Variance is the RMS value squared (σ^2), that is:

$$Variance = \sigma^2 \qquad \text{(D.3)}$$

If the average value was not removed from the signal before sampling, then the RMS value and variance are calculated as follows:

$$RMS = \sigma = \sqrt{\sum_{i=1}^{N} \frac{\left(x_i - \overline{x}\right)^2}{N}} \qquad \text{(D.4)}$$

$$Variance = \sigma^2 = \sum_{i=1}^{N} \frac{\left(x_i - \overline{x}\right)^2}{N} \qquad \text{(D.5)}$$

Another parameter of interest is one that describes the distribution of the data about its mean value. If one takes a set of N samples of random noise data and counts the number of times each value occurs, those values near the average or mean would occur most frequently. As one moves away from the mean value in either direction (above or below the mean), the number of occurrences decreases until at some distance from the mean value one finds no occurrences of the data. This is the basic concept of the amplitude probability distribution or APD. Figure D-2 illustrates a typical APD. A more familiar and general term for an APD is a histogram.

The function that describes the APD of a Gaussian signal $x(t)$ is written as:

$$p(x) = \frac{\exp\left(-x^2 / 2\sigma^2\right)}{\sigma\sqrt{2\pi}} \qquad \text{(D.6)}$$

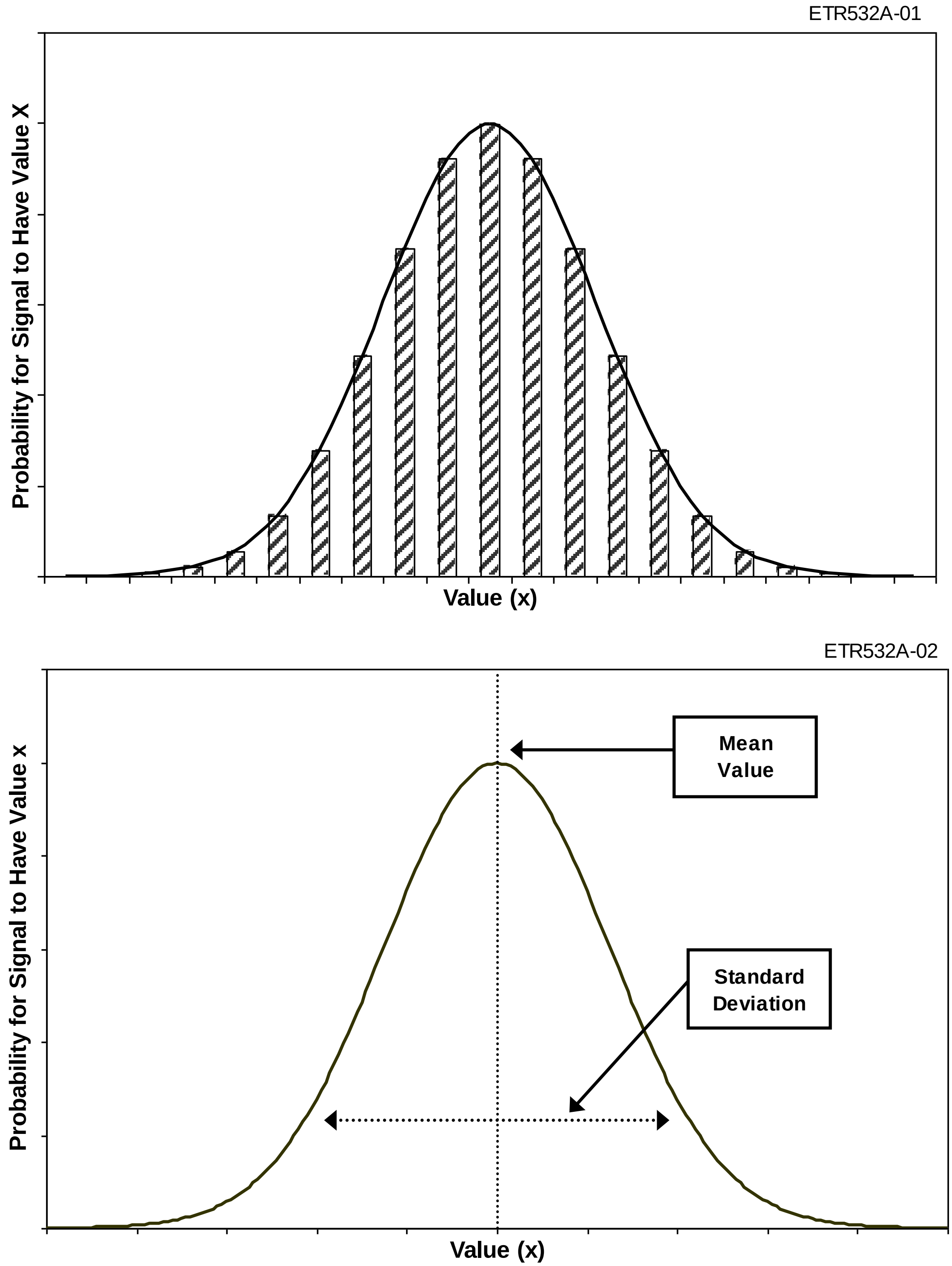

Figure D-2
Illustration of Histogram (top) and APD (bottom)

where σ is the RMS value of the signal $x(t)$. Figure D-2 represents the APD of a signal that has a Gaussian distribution described by Equation (D.6). The Gaussian distribution is also called a "normal" distribution. Almost all nuclear plant noise signals from properly operating sensors and systems should have Gaussian distributions. With this in mind, the Gaussian distribution (i.e., APD plot) is used as a means of qualifying the noise signal for analysis. A departure from Gaussian distribution can be determined by calculating the skewness of the signal. Skewness is an index of the symmetry of the signal or the behavior of the signal above and below the mean value. The skewness is computed as:

$$Skewness = \frac{1}{N} \sum_{i=1}^{N} \frac{x_i^{\,3}}{\sigma^3} \qquad \text{(D.7)}$$

Data which is symmetrical above and below its average value will have a skewness value of zero.

The APD described above quantifies the probability of a sample occurring with a value of "x". In some cases, it is desirable to look at the probability of a sample occurring with a value of "x or less". This is called the cumulative probability distribution function (CPDF), shown in Figure D-3 for a normal and a skewed signal. To better see small deviations from the Gaussian distribution, the CPDF is sometimes plotted as the number of standard deviations departure of the data value from the mean value. This is similar to using a special probability axis which causes the normal or Gaussian data to lie on a straight line. This process is also similar to plotting exponential data on semi-log paper to obtain a straight line. An example of this type of plot of the CPDF is shown in Figure D-4 for a normal (Gaussian) and a skewed set of random data. Figures D-3 and D-4 represent the same data sets. Note that the departures from Gaussian (dotted line) at the extreme ends are evident in the plot of Figure D-4.

Time Domain Analysis

In the time domain, correlation and autoregressive methods are used for analysis of noise data. The correlation function for a noise signal $x(t)$ is written as:

$$R_{xx}(\tau) = \frac{1}{T} \int_{-T/2}^{T/2} x(t)x(t-\tau)dt \qquad \text{(D.8)}$$

where $R_{xx}(\tau)$ is referred to as autocorrelation function, τ is a time lag, and T is the signal duration. The autocorrelation function describes the general dependence of the value of the data

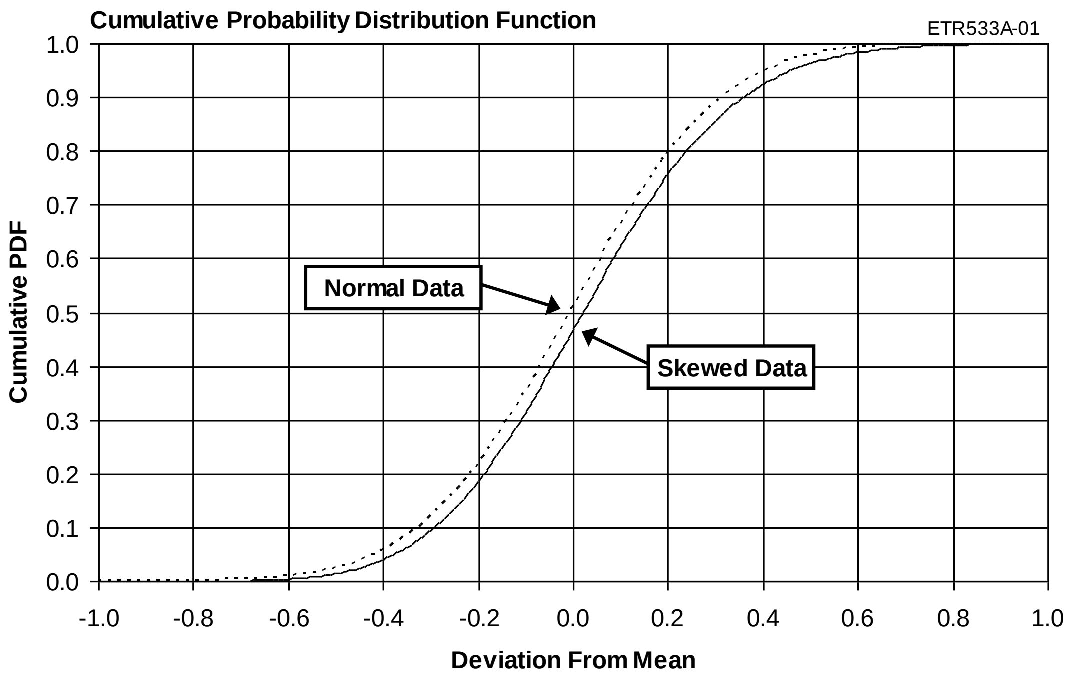

Figure D-3

CPDF for Normal and Skewed Noise Records

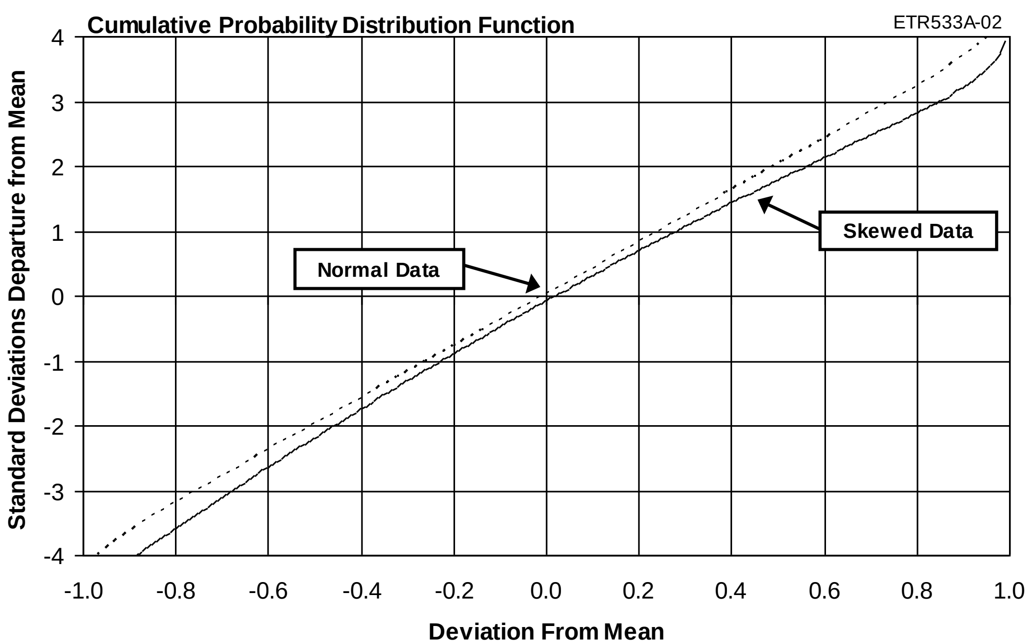

Figure D-4
Cummulative Probability Distribution

at one time on the values at another time. The function provides insight into the existence of periodic signal components in the random data and the nature of narrow and wideband noise properties. In order to obtain the correlation between two different signals x(t) and y(t), a function called cross-correlation is used. The cross-correlation function $R_{xy}(\tau)$ is written as:

$$R_{xy}(\tau) = \frac{1}{T}\int_{-T/2}^{T/2} x(t)y(t-\tau)dt \qquad \text{(D.9)}$$

The cross-correlation function describes the general dependence of the values of one set of data on the other. It is used for measurement of time lags in transport processes, determination of transmission path by observing multiple peaks in $R_{xy}(\tau)$, and detection and elimination of interfering noise. In the time domain analysis of sensor noise data, the correlation function is plotted versus time. The peak in the correlation plot identifies the time delay between the sensors, i.e. the propagation time of the noise between the two sensors. Figure D-5 illustrates the result of the cross-correlation of a pair of signals from two sensors in a nuclear power plant.

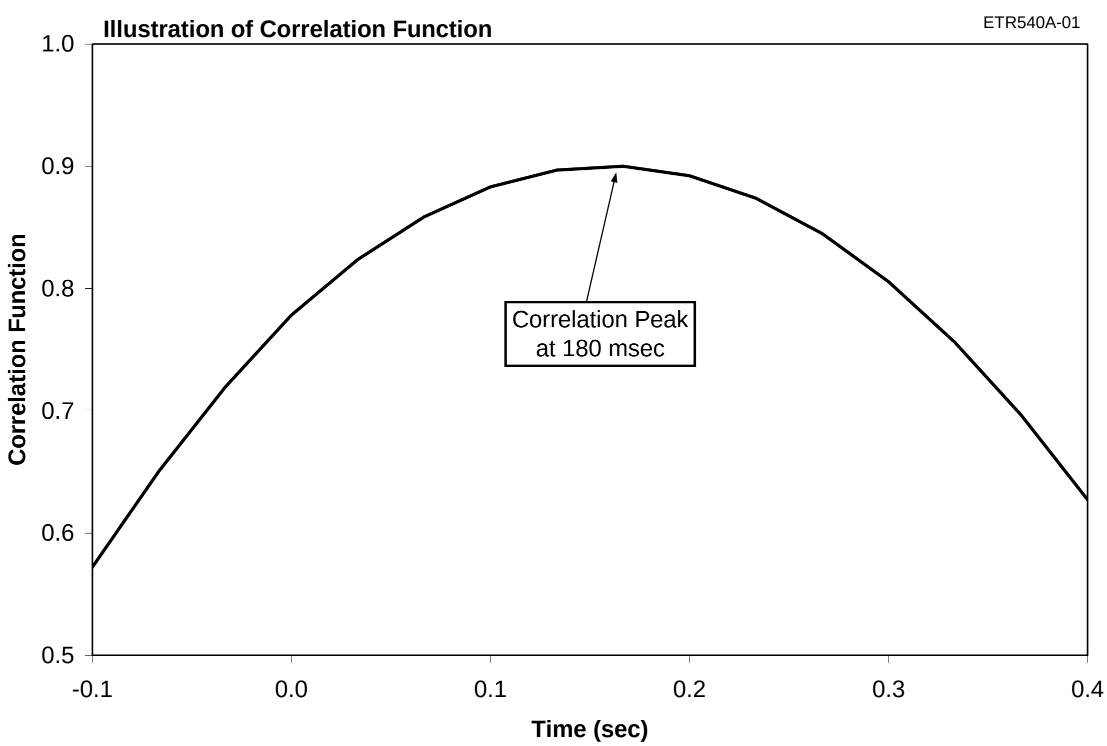

Figure 5
Plot of Correlation Function of a Pair of Signals from Two Sensors in a Nuclear Power Plant

__Frequency Domain Analysis__

Frequency domain techniques are a popular method for analysis of reactor noise signals. The frequency domain descriptors may be obtained from time domain correlation functions discussed above or from a direct Fourier transformation of the noise data. As in the time domain analysis, there are two groups of frequency domain descriptors. One group such as auto power spectral density (APSD) that is used for single signals, and another group such as cross power spectral density (CPSD) that is used for signal pairs. These frequency domain descriptors are related to their time domain counterparts through an integral function:

$$APSD = 2\int_{-\infty}^{\infty} R_{xx}(\tau) e^{-2\pi j f \tau}\, d\tau \qquad \text{(D.10)}$$

and

$$CPSD = 2\int_{-\infty}^{\infty} R_{xy}(\tau) e^{-2\pi j f \tau}\, d\tau \qquad \text{(D.11)}$$

Instead of integrating the correlation functions, the APSD and CPSD can be determined by the Fourier transform of the signal. For example, the APSD of $x(t)$ can be identified from:

$$APSD = \frac{2}{T}\left|\int_{-T/2}^{T/2} x(t) e^{-j2\pi f t}\, dt\right|^2 \qquad \text{(D.12)}$$

The physical significance of the APSD is that it provides a measure of signal power within discrete frequency bands over specified frequency ranges, i.e., it is the variance (σ^2) per unit narrow frequency band as a function of frequency.

It is customary to divide the values of the APSD and CPSD obtained from the above equations by the square or product of the steady state values of the signal to obtain normalized quantities. The normalized quantities are sometimes denoted as NPSD and NCPSD, but the terms PSD and CPSD (without the N) are the most common terms used for expressing these normalized quantities.

Two other useful frequency domain descriptors are the coherence and the phase angle between two signals. These descriptors can be identified from the PSD and CPSD of two signals *x* and *y* as follows:

$$Coherence = \gamma_{xy}^{\ 2} = \frac{(CPSD)^2}{(PSD)_x (PSD)_y} \qquad \text{(D.13)}$$

The coherence is a dimensionless quantity which defines the strength of the $x(t)$ and $y(t)$ relationship as a function of frequency. It has a value between zero and one, with one indicating that the relationship between x and y is linear time invariant.

$$0 \leq \gamma_{xy}{}^{2} \leq 1 \tag{D.14}$$

The phase is obtained from CPSD as:

$$\Phi(f) = \tan^{-1}\left[\frac{\mathrm{Im}(CPSD)}{\mathrm{Re}(CPSD)}\right] \tag{D.15}$$

where Im() and Re() represent the imaginary and real components of the CPSD function.

The phase spectrum of the Fourier transform of the sensor data can also be used to determine the transit or propagation time of noise between pairs of sensors. The slope of the phase plotted as a function of frequency is used to calculate the time delay as follows:

$$t = \frac{\delta\phi}{2\pi\delta f} = \frac{slope}{360}\text{, where } 2\pi\delta f t = \delta\phi \tag{D.16}$$

where t is the time separation of the correlated signals, $\delta\phi$ is the change in FFT phase, and δf is the frequency band of highest coherence. The slope is calculated over the region of the spectrum where the two data sequences are most coherent to avoid some of the effects of process variations not related to flow.

Auto Regression Modeling

Auto regression (AR) modeling, moving average (MA) modeling, and auto regressive moving average (ARMA) modeling are all related [1-6].

The AR model general equation is:

$$\mathrm{Y}_i = a_1\mathrm{Y}_{i-1} + a_2\mathrm{Y}_{i-2} + \cdots + a_p\mathrm{Y}_{i-p} + \mathrm{X}_i \tag{D.17}$$

where:

a_i's are the AR coefficients

Y_i is the data value at time i

X_i is the white noise input with mean=0 and constant variance σ^2

p is the AR model order.

The number of coefficients determines the order of the AR model. Future values are based on a combination of the previous data value and the white noise input.

An example of an AR model of order 3 is:

$$\mathrm{Y}_i = a_1 \mathrm{Y}_{i-1} + a_2 \mathrm{Y}_{i-2} + a_3 \mathrm{Y}_{i-3} + \mathrm{X}_i \qquad \text{(D.18)}$$

Here, future values are based on the prior three values.

As the AR order increases, the white noise input comprises less of the data and future data is composed of primarily of combinations of prior data values.

The MA model general equation is:

$$\mathrm{Y}_i = b_1 X_{i-1} + b_2 X_{i-2} + \cdots + b_p X_{i-p} + \mathrm{X}_i \qquad \text{(D.19)}$$

where:

b's are the MA coefficients

Y_i is the data value at time i

X_i is the white noise input with mean=0 and constant variance σ^2

p is the MA model order.

ARMA is then a combination of both AR and MA in the form:

$$\mathrm{Y}_i = a_1 \mathrm{Y}_{i-1} + a_2 \mathrm{Y}_{i-2} + \cdots + a_p \mathrm{Y}_{i-p} + b_1 X_{i-1} + b_2 X_{i-2} + \cdots + b_p X_{i-p} + \mathrm{X}_i \qquad \text{(D.20)}$$

where:

a's are the AR coefficients

b's are the MA coefficients

Y_i is the data value at time i

X_i is the white noise input with mean=0 and constant variance σ^2

p is the AR and MA model order.

The order for ARMA can be different for the AR and MA portions, but in practice the same order is typically used for both as shown in the equation above.

Power Spectral Density

The reason for creating an AR model is to obtain a good power spectral density (PSD) estimate based on the AR model. Typically a good AR estimate can be obtained from a small quantity of data.

The PSD of the AR model can be calculated directly from the AR coefficients by [4]:

$$PSD_{AR} = \frac{\sigma^2}{f_s \left| 1 + r_0 - \sum_{k=1}^{p} a_k e^{-2\pi jkf/f_s} \right|^2} \tag{D.23}$$

Optimum Order Selection

There are several classic criteria to evaluate the model order: Akaike, Bayes Probability, and Rissanen Minimum Descriptive Length (MDL). These are calculated as follows [1]:

$$Akaike(AIC) = N\ln\left(\sigma^2\right) + 2i \tag{D.24}$$

$$MDL = N\ln\left(\sigma^2\right) + i\ln(N) \tag{D.25}$$

$$Bayes = N\ln\left(\sigma^2\right) + i\left[\ln\left(N \times r_0/\sigma^2\right) - 1\right] \tag{D.26}$$

where

N = Samples

σ^2 = Residual variance

i = AR Order

r_0 = Auto correlation value at 0 time lag.

A comparison of these criteria versus model order shows that they find the optimal order at different places. The second part of the equation always increases with increasing model order. This attempts to identify the lowest possible model order that is suitable. The common component in these criteria is the first part of the equation based on the residual variance. In general, the best criteria overall is the MDL criteria.

Auto Regressive Methods

Some traditional AR methods are: Yule-Walker, Burg, Covariance, and Modified Covariance. Also, the Prony method is a traditional ARMA method. The Yule-Walker method was developed from a combination of work by British statistician G. Yule in 1927 on modeling sunspot data from 1749 to 1894 and work by Walker in 1931 [1]. Using a least square regression, they modeled future data on past data samples. The results of this work produced the Yule-Walker equations:

$$r_m = \sum_{j=1}^{p} a_j r_{m-j} \qquad \text{(D.27)}$$

This relates to the AR model of order 3 by:

$$\begin{bmatrix} r_1 \\ r_2 \\ r_3 \end{bmatrix} = \begin{bmatrix} r_0 & r_{-1} & r_{-2} \\ r_1 & r_0 & r_{-1} \\ r_2 & r_1 & r_0 \end{bmatrix} \bullet \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} \qquad \text{(D.28)}$$

This makes the Yule-Walker method the best suited for analyzing multiple blocks of data because the autocorrelation coefficients can be calculated for each block and then averaged to determine an average set of autocorrelation coefficients for the data set. These averaged autocorrelation coefficients are then used to solve the AR coefficients for various model orders.

The Burg method was developed by John Burg in 1967. The Burg method estimates the reflection coefficients directly and avoids calculating the autocorrelation function. It attempts to minimize both forward and backward prediction errors to solve for the AR coefficients by using least squares recursion. The Burg method is good at identifying closely spaced sinusoids in signals with low noise levels and also modeling well with short data sets [1]. The accuracy of the Burg method decreases as the model order becomes high or for long data sets.

The covariance and modified covariance methods use covariance to solve for the AR coefficients. The covariance method attempts to minimize the forward prediction error. The modified covariance attempts to minimize both the forward and backward prediction error [1]. Similar to the Burg method, they estimate the coefficients directly from the data and do not calculate the autocorrelation function.

The Prony method of ARMA is based on work by Gaspard Riche, Baron de Prony in 1795 that attempted to model expansion of gases by sums of damped exponentials. The modern Prony method of ARMA first models a portion of the data with an AR model, and then models the residual noise with an MA model. The combination of these two methods should allow good spectral estimation with a much smaller model order than either AR or MA alone [1].

References

1. *Digital Spectral Analysis*. Marple, S. L., Prentice-Hall, Inc.: 1987.

2. *Power Reactor Noise*. Thie, J.A., American Nuclear Society: 1981.

3. *Evaluation of the Autoregression Time-series Model for Analysis of a Noisy Signal*. Allen, J.W., Progress in Nuclear Energy, Volume 1, pp. 603-613: 1977.

4. *Signal Processing Toolbox User's Guide Version 6*. The Mathworks, Inc., The Mathworks, Inc.: 2006.

5. *Why Yule-Walker Should not be Used for Autoregressive Modelling*. de Hoon, M.J.L., van der Hagen, T.H.J.J., Schoonewelle, H., van Dam, H., Annals of Nuclear Energy, Volume 23, Number 15, pp. 1219-1228: 1996.

6. *Digital Signal Processing: Principles, Algorithms, and Applications*. Proakis, J.G., and Manolakis, D.G., Prentice-Hall, Inc.: 1996.

APPENDIX E

An Integrated System for Static and Dynamic On-Line Monitoring of Nuclear Power Plant Systems and Components

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AN INTEGRATED SYSTEM FOR STATIC AND DYNAMIC ON-LINE MONITORING OF NUCLEAR POWER PLANT SYSTEMS AND COMPONENTS

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ABSTRACT

Nuclear power plants (NPPs) are instrumented with numerous sensors to provide data for control, assurance of safety, and plant operations. Many of the signals from these sensors can be monitored while the plant is on-line to verify the accuracy and reliability of the sensors themselves, and as importantly, for plant diagnostics, aging management, and health monitoring. This can be accomplished by taking full advantage of the information that can be extracted from the outputs of these sensors.

The steady-state value of the sensor output is referred to as the *static* component, while the small fluctuations inherently present are known as the *dynamic* component of the signal. When used together, static and dynamic analysis techniques can help verify the health of the plant; however, they are often applied separately by different individuals and organizations, and as a result, they do not provide a complete picture of plant health. To help close this gap, the authors developed a system that integrates static and dynamic on-line monitoring (OLM) techniques as part of a Small Business Innovation Research (SBIR) project sponsored by the U.S. Department of Energy (DOE). In particular, the OLM system developed for this project integrates two important classes of static and dynamic OLM techniques referred to as *process modeling* and *noise analysis*. These techniques can be applied using data from existing sensors in NPPs, enabling centralized analysis for applications such as on-line calibration monitoring of pressure, level, and flow transmitters, equipment condition monitoring, and dynamic sensor response testing. This paper provides details into the research and development of the OLM system and demonstrates results of testing the system on actual operating NPP data provided by several plants that actively participated in the project.

Key Words: on-line monitoring, plant computer data, calibration monitoring, noise analysis

1 INTRODUCTION

As the current generation of nuclear power plants (NPPs) have passed mid-life, increased monitoring of their health is critical to safe operation. This is especially true now that license renewal of NPPs has accelerated in the United States, allowing plants to operate up to 60 years. Furthermore, many utilities are maximizing their power output through uprating projects and retrofits, which put additional stresses on the plant equipment and make them more vulnerable to the effects of aging, degradation, and failure. In the meantime, the nuclear power industry is working to reduce generation costs by adopting condition-based maintenance strategies and automating testing activities.

Prior to the work done for the project described in this paper, the foundation for much of the required technology had already been established, but the various technologies had yet to be assembled into an integrated on-line monitoring system to facilitate their use in NPPs. As such, the primary objective of this project was to design and develop such a system and demonstrate its use in an operating NPP.

The term on-line monitoring (OLM) is used to describe methods for evaluating the health and reliability of nuclear plant sensors, processes, and equipment from data acquired while the plant is operating. NPPs are instrumented with numerous sensors to provide data for control, assurance of safety, and plant operations. Many of the signals from these sensors can be monitored while the plant is on-line to verify the accuracy and reliability of the sensors themselves, and as importantly, for plant diagnostics, aging management, and health monitoring. This can be accomplished by taking full advantage of the information that can be extracted from the outputs of these sensors.

2 STATIC AND DYNAMIC ON-LINE MONITORING

Normally, while the plant is operating, a sensor's output will have a steady-state value corresponding to the process parameter indicated by the sensor. This steady-state value is often referred to as the *static* component, or DC value. In addition to the static component, a small fluctuating signal is naturally present on the sensor output. This fluctuating signal, which is known as the signal's *dynamic* component, or AC signal, stems from inherent fluctuations in the process parameter caused by turbulence, random flux, random heat transfer, vibration, and other effects.

The types of OLM applications in NPPs are in large part determined by the sampling rates available for data acquisition. OLM applications that use static data, such as on-line calibration monitoring of pressure transmitters, typically require sampling rates up to 1 Hz, while OLM applications using dynamic data such as sensor response time testing use sampling rates in the 1 kHz range. Table 1 lists several OLM applications that can be implemented by utilizing static and dynamic data.

The static and dynamic components of the sensor output each contain different information about the process being measured, and as such, can be used for a number of OLM applications. For example, applications that monitor for gradual changes in the process over the fuel cycle, such as sensor calibration monitoring, make use of the static component. On the other hand, applications that monitor fast changing events, such as core barrel motion, use the information in the dynamic component that provides signal bandwidth information. In particular, the system developed for this project integrates two important classes of static and dynamic OLM techniques referred to as *process modeling* and *noise analysis* [1] that can be applied using data from existing sensors in NPPs. Figure 1 illustrates the concept of the OLM system that was designed, developed, and implemented as part of this project and its relationship with existing NPP sensors and plant systems.

Table 1. OLM applications using static and dynamic data

Static Data	Dynamic Data
On-Line Calibration Monitoring of Pressure Transmitters	Dynamic Response of Pressure Transmitters
RTD Cross-Calibration	Predictive Maintenance of Reactor Internals
Thermocouple Cross-Calibration	Detection of Core Flow Anomalies
Equipment Condition Assessment	Life Extension of Neutron Detectors

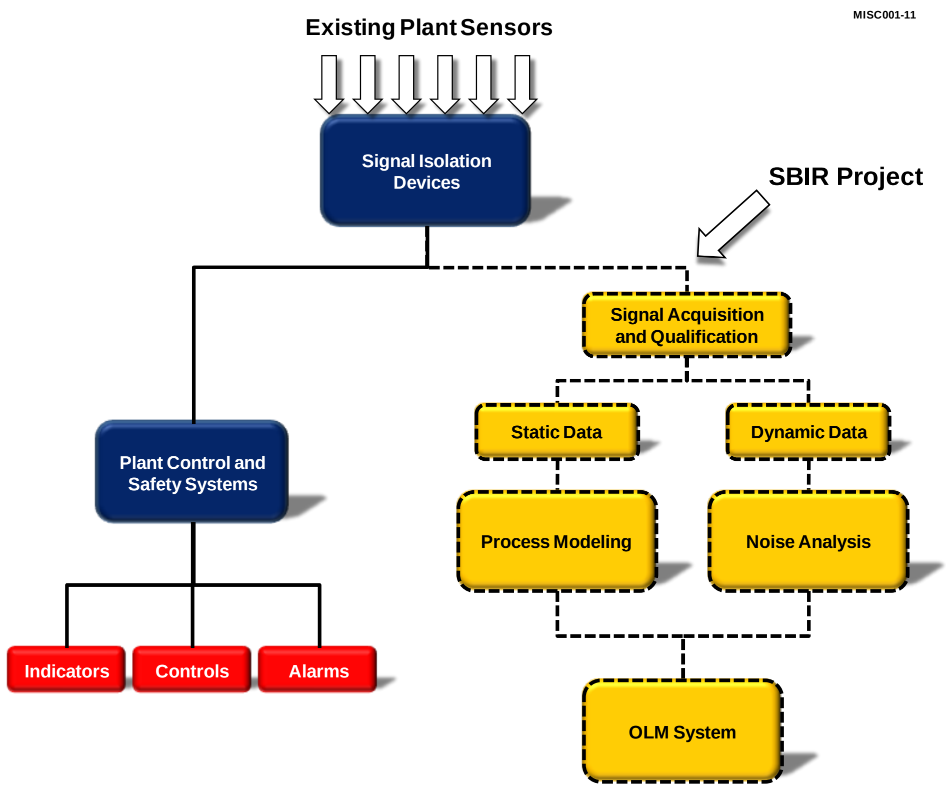

Figure 1. OLM system concept

2.1 Static Data and Process Modeling

Static data is generally retrieved from the plant computer and is sampled at various rates, 1 Hz being typical. This data can be used to perform analytical modeling of the processes and sensors that are being monitored. A primary operation of any static data analysis performed for an NPP is to detect transmitters or processes that may be drifting from their normal operating states. However, it is often difficult in practice for static analysis algorithms to separate instrument drift from process drift. Analytical models provide one solution for accomplishing this in NPPs.

To separate instrument drift from process drift, or to establish a reference for detecting drift, a number of techniques may be used depending on the process and number of instruments that can be monitored simultaneously. For example, if redundant instruments are used to measure the same process parameter, then the average reading of the redundant instruments may be used as the reference for detecting drift. In this case, the normal outputs of the redundant instruments are scanned and averaged. This average value is subtracted from the reading of each redundant instrument to identify the deviation of the instrument from the average. The deviation from the average for each transmitter can then be evaluated versus a limit, to determine if the sensor is drifting. Figure 2 shows an example of the average deviations of four NPP pressure transmitters over a period of six years.

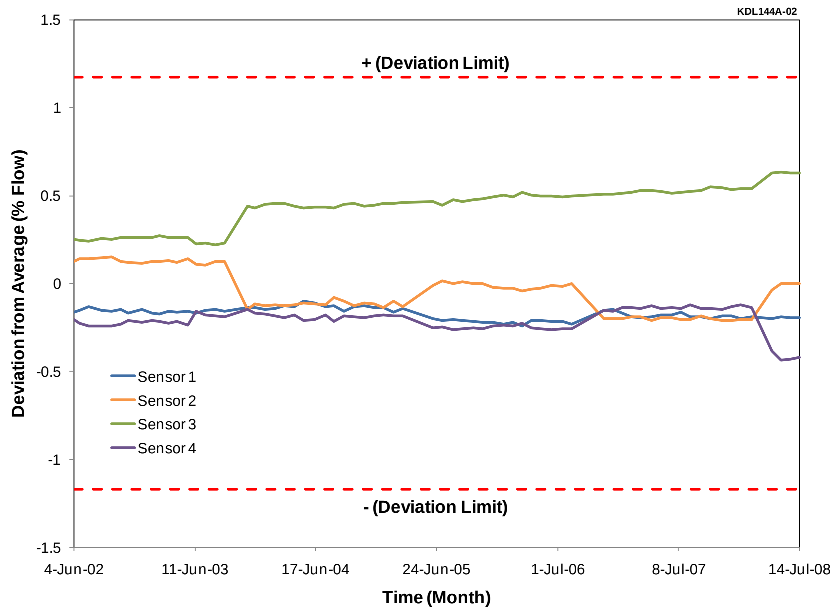

Figure 2. Deviation from average of four pressure transmitters

Although averaging techniques have proven successful for determining drift in nuclear power plants [2-6], they are not always adequate to estimate the process parameter in cases where there is little or no redundancy. In this case, static analysis algorithms must incorporate a methodology to produce process estimates from diverse signals. Analytical modeling can be used to provide process estimates from diverse signals where the amount of redundancy is not sufficient for averaging techniques. In other words, averaging techniques can be used to form a process estimate where redundant signals are available, and analytical modeling techniques are used to calculate a process estimate from a group of physically related diverse signals.

2.2 Dynamic Data and Noise Analysis

Dynamic data in general cannot be retrieved from the plant computer, as the sampling rate of most plant computers is not high enough to capture the high frequency components of the sensor signal. A dedicated data acquisition unit can be used to acquire the high frequency data for dynamic analysis, typically in the 1 kHz range. Primarily, this data is used to perform noise analysis on pressure transmitters to determine the response time of the sensors.

Noise analysis includes fitting an equation to the relevant portion of the power spectral density (PSD) plot calculated from the data (to estimate the dynamic response of the sensor), and performing various statistical tests. The dynamic analysis performed by the OLM system is largely based on performing an auto-regressive (AR) model analysis of the time series data [7]. The PSD of the data, along with other factors such as the step response, can be calculated from the AR model. This process is described in more detail in the next section.

In the past, performing AR analysis of dynamic NPP sensor data required expert knowledge and complicated software programs. One of the sub-goals of this project was to simplify the process of performing AR analysis so that it could be automated and used to provide reliable dynamic evaluation of NPP sensors. Once the analysis is completed, the results can be saved to the OLM system database. As the same sensors (and sensors of the same type) are tested repeatedly over time, the results of the testing can be trended to help identify sensor or sensing line degradation and other anomalies that may occur.

3 INTEGRATED ON-LINE MONITORING SYSTEM

When used together, static and dynamic OLM techniques can help verify the health of the plant; however, they are often applied separately by different individuals and organizations, and as a result, they do not provide a complete picture of plant health. To help close this gap, the authors developed a system that integrates static and dynamic OLM techniques of process modeling and noise analysis that can be applied using data from existing sensors in NPPs, enabling centralized analysis for applications such as those listed in Table 1 above.

A key component of the research was developing a framework to provide the foundation for the practical integration and implementation of the various OLM analysis techniques in existing and next generation NPPs. As such, the technical scope of the project included completing several objectives including:

- Identifying sources of data, such as the plant computer, that are typically available in operating NPPs, and determining any limitations in the data from these sources that might affect the OLM analysis.
- Designing and developing an automated data acquisition system to provide the necessary capabilities for data extraction for cases in which the existing plant computer data is not sufficient for OLM.
- Identifying data qualification and data analysis techniques that are best suited for establishing instrument reliability and plant health monitoring.
- Designing, developing, and testing a system comprised of both hardware and software modules that integrates all the necessary components of OLM including data acquisition, data qualification, data analysis, and plant health status reporting and can be controlled from a single personal computer (PC) platform.
- Validating the OLM system modules in a laboratory test loop environment.
- Implementing and demonstrating the OLM system in an operating NPP.

As a result of the research and development (R&D) performed during this project, an OLM system was constructed that consisted of several software/hardware modules integrated into one common framework. The parts of this framework are illustrated in Figure 3, with the main components described in detail in the following sections.

3.1 Data Acquisition

Most of the data collected by the plant computer is stored on a plant historian. These historians are designed to compress data to facilitate storage and retrieval. As such, the data is typically stored at slower rates than may be required for dynamic performance evaluations and some other diagnostics. However, most of these historians can be configured to supply data at faster rates for shorter periods of time. Even so, it is often the case that a sample rate much higher than the plant computer can provide is necessary to assess the dynamic performance of a sensor.

The Data Acquisition module allows the user the acquire data from the plant computer for static analysis, and/or from a dedicated data acquisition system for use with dynamic analysis techniques. To obtain static data, a data bridge software module was incorporated into the OLM system that is capable of retrieving data from common plant data historians such as the PI system, which is a software product from the OSIsoft Company, or the eDNA system, which is a software product from the InStep Software Company.

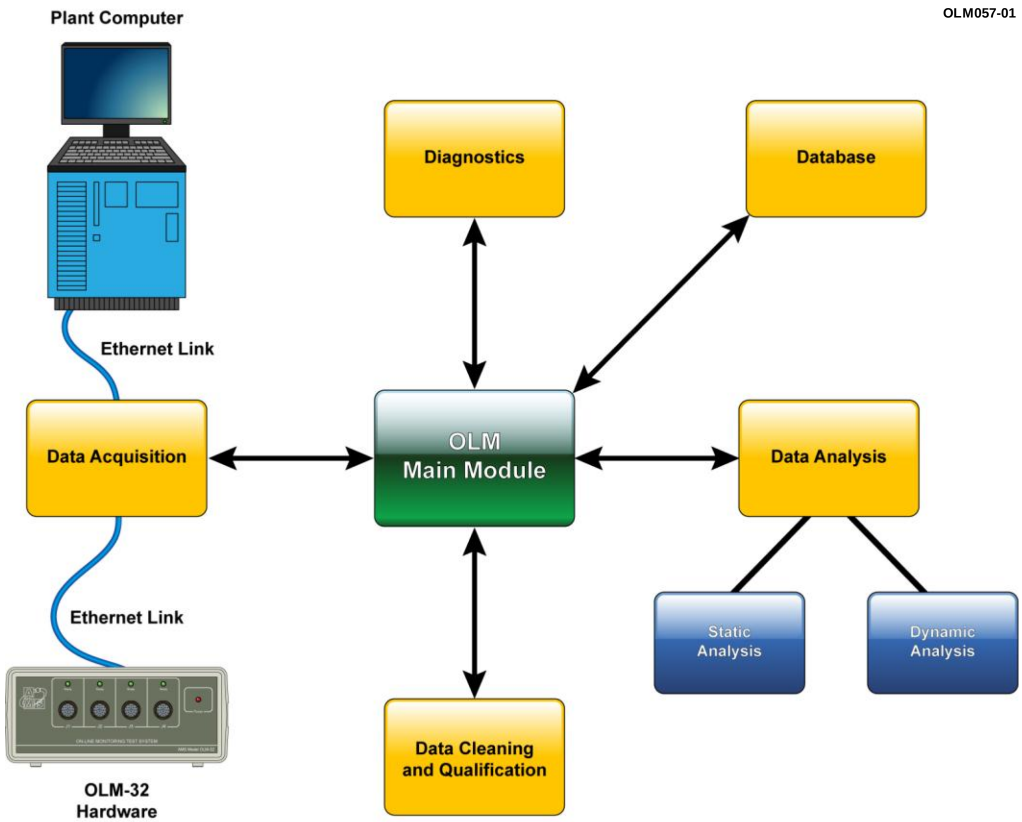

Figure 3. Block diagram of the OLM system

Dynamic data acquisition is made possible by the OLM system interface to a dedicated high-speed data acquisition system called the OLM-32, which is able to acquire up to 32 signals simultaneously at rates up to 50 kHz. The OLM system is interfaced to the plant computer (via the data bridge) and the OLM-32 data acquisition system through a TCP/IP connection provided over an Ethernet network link. This allows the OLM system to acquire and store both static and dynamic data from a central location. Alternatively, dynamic data acquisition with the OLM-32 may also be accomplished using a laptop computer or other portable device.

3.2 Data Cleaning and Qualification

Once the data has been acquired, either from the plant computer or through the dedicated data acquisition system, it must be cleaned and qualified. Data cleaning involves removing artifacts such as gaps, and/or ‘dead’ spots in the data that can hinder analysis. Data qualification, on the other hand, involves analyzing the data using various statistical descriptors such as mean, variance, and kurtosis, as well as amplitude probability distribution (APD) plots to verify that the data does not deviate significantly from its historical baseline.

3.3 Static Data Analysis

This module provides software interfaces and algorithms for performing sensor and process drift detection using redundant sensor averaging and analytical modeling techniques. The OLM system uses kernel regression [8] as the algorithm for static process modeling. For a comprehensive treatment of kernel regression as applied to modeling NPP processes, the reader is referred to [9]. Basically, the process of training a kernel regression model involves choosing the various kernel regression parameters and evaluating the resulting model. Once these parameters have been chosen, and the modeling metrics are deemed satisfactory, the modeling parameters can be saved to the OLM system database for later testing.

New data acquired from the plant computer is evaluated against the models stored in the OLM system database. The OLM system allows the user to load a set of data and view the residuals calculated by the kernel regression algorithm. Each sensor in the models can be viewed versus its acceptance limits as configured by the user. The results can then be saved to the OLM system database for later viewing and trending.

3.4 Dynamic Data Analysis

This module provides software interfaces and techniques for analyzing high-frequency data for sensor response time testing, and on-line detection of sensing-line voids, blockages, and leaks. The primary tool used to evaluate the dynamic response of the sensor data is auto-regressive (AR) modeling [7]. 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 that was acquired with the OLM-32 data acquisition system discussed above was trimmed to form narrow band data to maximize the efficiency of the AR modeling. In this way, the approach was 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.

The PSD shown in Figure 4 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

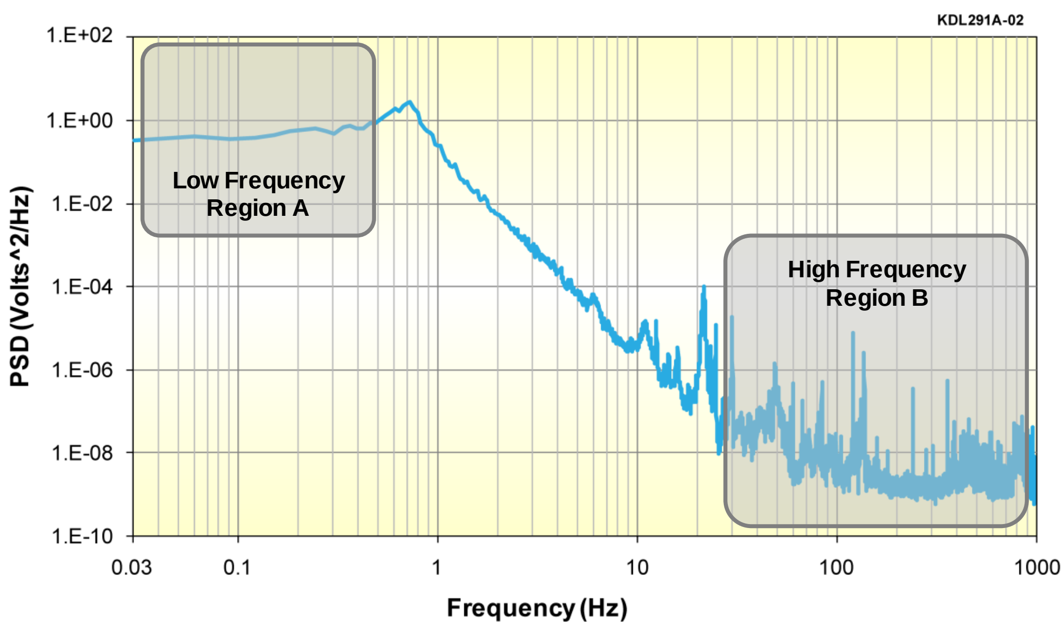

Figure 4. Wide band PSD with AR analysis problem regions identified

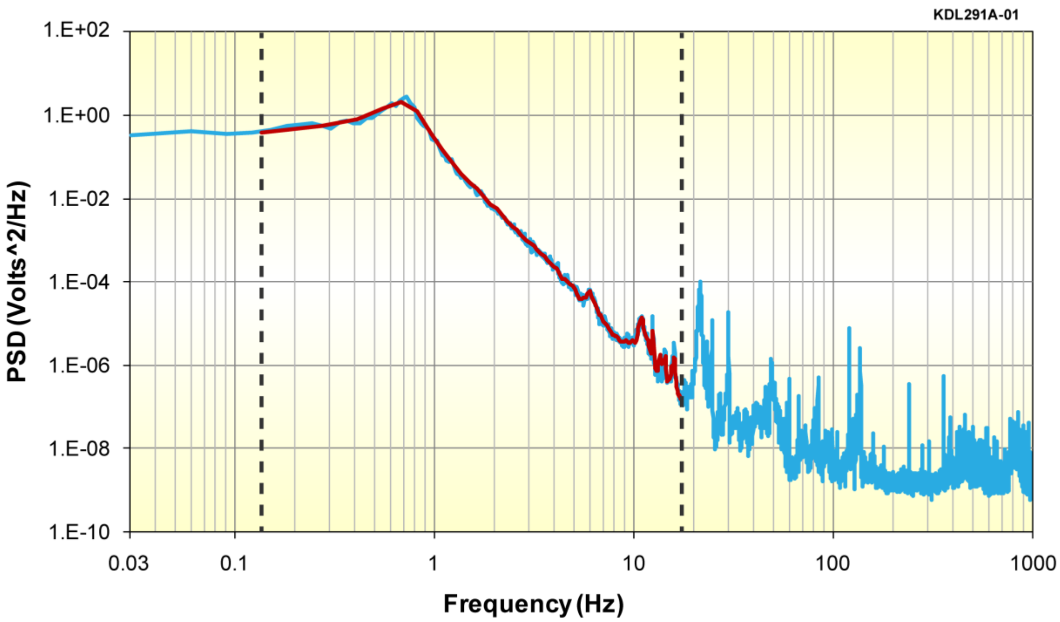

Figure 5. Narrow band dynamic analysis window selection with its PSD overlaid

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 5.

After the narrow band data is selected, it is analyzed by the various AR methods and polynomial order sizes. 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.

3.5 Database

In order for the OLM system to operate, a means for centralized storage of configuration settings, sensor information, and results must be provided. The OLM system database serves as a central repository for the various configuration settings, sensor information, and results used and produced by the OLM system. To help simplify the storage and retrieval of all of this information, a Microsoft SQL Server database was incorporated into the design of the OLM system. Virtually every part of the OLM system uses the database for storing and retrieving settings, data, results, and other information. A diagram of the OLM database and the types of information that can be stored to and retrieved from it is shown in Figure 6.

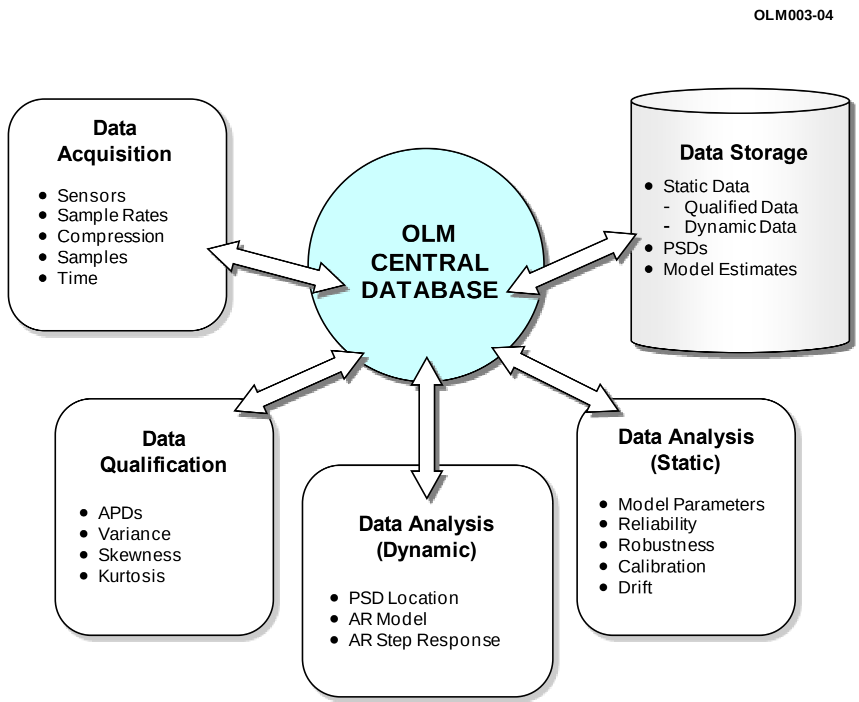

Figure 6. OLM database diagram

3.6 Diagnostics

This module allows the user to view at-a-glance the status of the various plant systems and components that are being monitored by the OLM system. The Diagnostics module displays and integrates the analysis results of all static and dynamic testing performed by the OLM system. The results of various types of static and dynamic analysis that have been performed on the plant sensors can be loaded from the OLM system database and displayed. The health of each sensor is displayed in terms of static data tests (such as process modeling), and dynamic tests (such as dynamic response).

4 RESULTS

Throughout the course of the project, several nuclear power plants actively participated by providing plant computer data, engineering resources, and plant access to test the implementation of the OLM system. As an example of static analysis results, consider a steam generator model made for Plant 1. A model for each of the steam generators at Plant 1 was created and tested using the OLM system. The Steam Generator model consists of flow, level, pressure, and temperature sensors. The model was trained on a 12-hour sample of data, and then evaluated with 11 months of test data that followed the training sample. Figure 7 shows test results for the flow, level, and pressure transmitters. The test results show the average residuals for each of the sets of transmitters in the model versus their acceptance limits. As shown in the figure, most of the residuals remain within the acceptance limits. The exception is the Steam Generator A level transmitter number 4 that drifts beyond its acceptance limits over the cycle. In the case of this transmitter, manual calibrations performed during the outage confirmed that the transmitter had drifted over the cycle and required adjustment. Similarly, the transmitters that did not show drift beyond their OLM acceptance limits did not require manual adjustments.

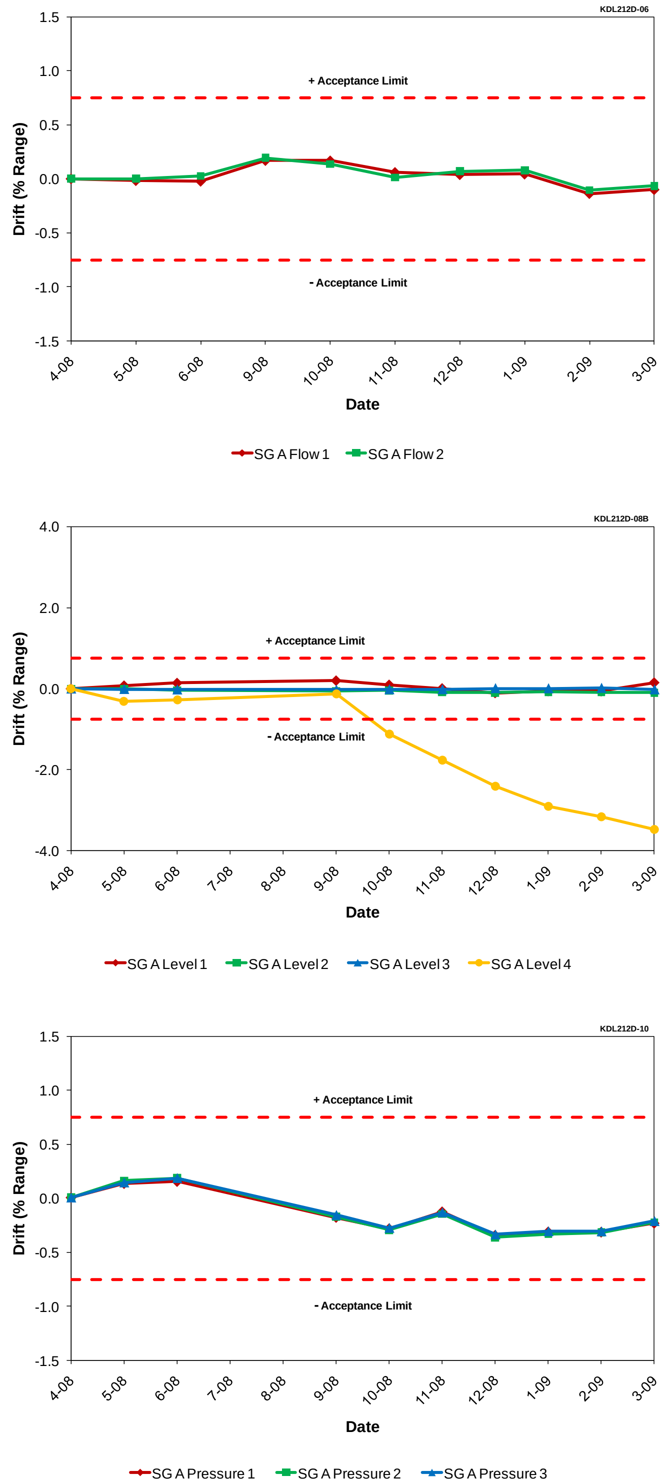

Figure 7. Plant 1 Steam Generator A analytical modeling results for flow, level, and pressure

For dynamic analysis, the AR PSDs are compared and the RMS error of the PSD difference is used to quantify the difference. An example of this is shown in Figure 8 for data taken at Plant 2 as part of the OLM project. This data shows a degraded PSD caused by a partially-blocked sensing line before the blockage was removed, and the resulting PSD after the line was cleared. In this case, as shown in the figure, the change in PSD creates a large error in the AR PSD Difference plot, and results in a large RMS error that is used to automatically flag this sensor as having a dynamic problem. With the normal PSD stored in the OLM system as a baseline for this transmitter, subsequent tests can be compared to it in order to detect anomalies.

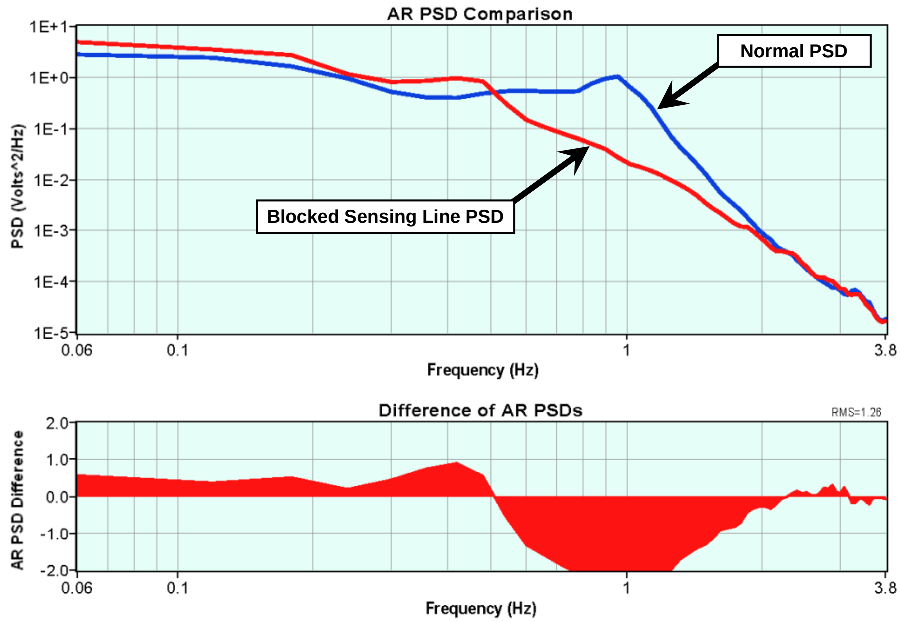

Figure 8. Example of dynamic analysis comparison results

5 CONCLUSIONS

This paper provides details into the research and development of an OLM system that integrates static and dynamic analysis techniques to verify the accuracy and reliability of NPP systems and components. The paper also provides results of testing the OLM system on actual operating NPP data provided by several plants that actively participated in the project.

After the OLM system was developed and tested in a laboratory environment, it was demonstrated with data acquired from several operating nuclear power plants. Both static and dynamic analysis techniques were demonstrated and showed good results in verifying the health and performance status of NPP systems and components.

Full plant implementation of the OLM system has been shown to have a substantial direct economic impact. Significant gains in indirect benefits, such as avoidance of forced outages, reduction of maintenance-induced damage to plant equipment, and improved plant safety and availability, could also be realized with implementation of the OLM system.

6 ACKNOWLEDGMENTS AND DISCLAIMER

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7 REFERENCES

1. H. M. Hashemian, "The state of the art in nuclear power plant instrumentation and control," *International Journal of Nuclear Energy Science and Technology*, Volume 4, Number 4 (2009).
2. *Plant Application of On-Line Monitoring for Calibration Interval Extension of Safety-Related Instruments: Volume 1*, EPRI, Palo Alto, CA USA and British Energy Group PLC, Suffolk, UK (2006). 1013486.
3. *Plant Application of On-Line Monitoring for Calibration Interval Extension of Safety-Related Instruments: Volume 2*, EPRI, Palo Alto, CA USA and British Energy Group PLC, Suffolk, UK (2006). 1013486.
4. *Plant Application of On-Line Monitoring for Calibration Interval Extension of Safety-Related Instruments: Volume 3: 2007 Update Report*, EPRI, Palo Alto, CA USA and British Energy Group PLC, Suffolk, UK (2007). 1015173.
5. *Plant Application of On-Line Monitoring for Calibration Interval Extension of Safety-Related Instruments: Volume 4: 2008 Update Report*, EPRI, Palo Alto, CA USA and British Energy, Suffolk, UK (2008). 1016723.
6. *Implementation of On-Line Monitoring to Extend the Calibration Interval of Pressure Transmitters in Nuclear Power Plants*, EPRI, Palo Alto, CA USA (2009). 1019188.
7. S. L. Marple, *Digital Spectral Analysis*, Prentice-Hall, Inc., Upper Saddle River, NJ USA (1987).
8. Atkeson, C. G., A.W. Moore, S. Schaal, "Locally Weighted Learning," *Artificial Intelligence Review*, Volume 11, Number 1-5, pp.11-73 (1997).
9. *Technical Review of On-Line Monitoring Techniques for Performance Assessment Volume 1: State of the Art*, U.S. Nuclear Regulatory Commission, Washington, D.C. USA (2006). NUREG/CR-6895, Vol.1 (ADAMS accession number ML060610394)

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