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INSTRUMENT CALIBRATION VERIFICATION

A Thesis

Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

John R. Olvera

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ABSTRACT

The redundant sensors typically found in nuclear power plants present an opportunity for verifying the calibration of sensors using non-intrusive signal validation techniques. Such techniques allow periodic surveillance (online or offline) that can quantitatively trend the performance characteristics of sensors. This allows I&C personnel to (1) identify incipient calibration failures, (2) identify sensors with chronic calibration drift problems, (3) prioritize maintenance activities, and (4) potentially adjust calibration schedules based on the historical behavior of sensors. A consistency checking algorithm compares the signals from redundant sensors against their respective tolerances to calculate a process variable estimate, and to generate a sensor inconsistency index. A data-driven empirical modeling scheme is used to provide an additional, diverse, point of redundancy, and to check against possible common mode calibration failures. A sequential probability ratio test is applied to generate two additional performance characteristics that aid in tracking and predicting calibration drift. Application of the methodology to plant sensor data with a bias error artificially added to one of the signals demonstrates an ability to detect the error within the prescribed tolerances of the sensors.

TABLE OF CONTENTS

1. INTRODUCTION 1
   - 1.1 Motivation for this Study 1
   - 1.2 Problem Statement and Overview of the Methodology 3
   - 1.3 Contributions of the Thesis 7
   - 1.4 Organization of the Thesis 7

2. CALIBRATION REQUIREMENTS 9
   - 2.1 Regulatory Requirements 9
   - 2.2 Codes and Standards 10
   - 2.3 Instrument Tolerances 11

3. PROCESS VARIABLE ESTIMATION 14
   - 3.1 Introduction 14
   - 3.2 Generalized Consistency Checking 16
   - 3.3 Process Empirical Modeling 23
   - 3.4 Evaluation of the Error Bound of Process Variable Estimates . . . 26

4. DETERMINATION OF SIGNAL DEVIATIONS FROM PROCESS VARIABLE ESTIMATE 40
   - 4.1 Introduction 40
   - 4.2 Sensor Statistics 41
   - 4.3 Cumulative Inconsistency Index 45
   - 4.4 Sequential Probability Ratio Test 47

5. EVALUATION OF CALIBRATION ADEQUACY 62
   - 5.1 Introduction 62
   - 5.2 Fuzzy Membership Functions 63
   - 5.3 Signal Tolerance for Calibration 69
   - 5.4 Sensor Adequacy Using Fuzzy Membership Functions 73

6. APPLICATION OF THE METHODOLOGY 82
   - 6.1 Description of Sensor Data 82
   - 6.2 Description of the Test Cases 92
   - 6.3 Results of the Test Cases 97

7. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK 135
   - 7.1 Summary and Conclusions 135
   - 7.2 Recommendations for Future Work 137

REFERENCES 139

APPENDICES 142
APPENDIX A - Description of Software 143
APPENDIX B - Listing of Code 150

LIST OF FIGURES

Figure 2.1	Example of Relationship Between Nominal Protection System Setpoints and Limits of Safe Conditions. (reference [5])	12
Figure 3.1	Example Density Functions of Four Normal Redundant Sensors	18
Figure 3.2	Example Density Functions of Three Normal and One Degraded Sensor	18
Figure 3.3	GCC Cumulative Inconsistency Indices - Example 1	19
Figure 3.4	Example of a Z-number Used as a GCC Weighting Function	22
Figure 3.5	Nuclear Power Range Monitor GCC Estimate vs. Measurement	22
Figure 3.6	Input/Output Relationship in a PEM Model	25
Figure 3.7	PEM Estimate vs. Reactor Power Measurements.	25
Figure 3.8	Example of a Mean Estimator Using Two Normal Sensors.	31
Figure 3.9	Example of a Mean Estimator With One Normal and One Degraded Sensor.	32
Figure 3.10	Example Distributions Of Three Normal And One Faulted Sensor.	34
Figure 3.11	Comparison of a GCC Estimate vs. a Mean Estimate	35
Figure 3.12	Effect of Faulted Sensor Error on the Process Variable Estimate.	37
Figure 4.1	Effect of Faulted Sensor Error on the Bias of All Sensors	44
Figure 4.2	Effect of Faulted Sensor Error on the SII of all Sensors.	48
Figure 4.3	Relationship Between the False and Missed Alarm Probabilities.	53
Figure 4.4	Example of SPRT Application to the Artificial Sensor Data Example.	56
Figure 4.5	Effect of Faulted Sensor Error on the MSTDN of all Sensors.	58
Figure 4.6	Effect of Faulted Sensor Error on the MSTDD for all Sensors.	59
Figure 4.7	Example of an SPRT Trend Using a Ramped Sensor Bias	61
Figure 5.1	Example of a π-Number as a Membership Function for Sensor Bias.	67
Figure 5.2	Example of a Z-Number Used as a GCC Weighting Function.	68
Figure 5.3	Behavior of the MSTDN and the MSTDD for the Example of Four Artificial Sensors.	76
Figure 5.4	Sensor Bias and Sensor Bias Index for the Artificial Sensor Case.	78
Figure 5.5	Signal Inconsistency Index (SII) and SII Index for the Artificial Sensor Case.	79
Figure 5.6	MSTDN and MSTDN Index for the Artificial Sensor Case.	80
Figure 5.7	MSTDD and MSTDD Index for the Artificial Sensor Case.	81
Figure 6.1	Steady-State Measurement from a Neutron Power Range Monitor.	84
Figure 6.2	Normalized Frequency Histogram for Neutron Power Range Sensors.	85

Figure 6.3 Reactor Power Data Used as the PEM Model Output. 88
Figure 6.4 Pressurizer Level Data Used as a PEM Model Input. 89
Figure 6.5 Cold Leg Temperature Data Used as a PEM Model Input. 89
Figure 6.6 Hot Leg Temperature Data Used as a PEM Model Input. 90
Figure 6.7 Main Steam Pressure Used as a PEM Model Input. 90
Figure 6.8 Steady State PEM Estimate vs. Neutron Power Range Monitor. . 91
Figure 6.9 GCC Estimate for Case I. 100
Figure 6.10 SPRT Results of Nuclear Power Range Monitors for Case I. . . . 101
Figure 6.11 GCC Estimate for Case II. 107
Figure 6.12 GCC Results of Nuclear Power Range Monitors for Case II. . . . 108
Figure 6.13 SPRT Results of Nuclear Power Range Monitors for Case II. . . . 111
Figure 6.14 GCC Estimate for Case III. 117
Figure 6.15 GCC Results of Nuclear Power Range Monitors for Case III. . . . 118
Figure 6.16 SPRT Results of Nuclear Power Range Monitors for Case III. . . 121
Figure 6.17 SPRT Results of Nuclear Power Range Monitors for Case IV. . . 125
Figure A.1 Initial Input Window for the ICVS. 145
Figure A.2 Input Menu for the ICVS. 145
Figure A.3 Child Windows Containing ICVS Results 148
Figure A.4 Expanded Child Window Containing the ICVS Summary. 148

LIST OF TABLES

Table 4.1	Sensor Statistics for the Artificial Sensor Data Example	43
Table 4.2	GCC Results for the Artificial Sensor Data Example	46
Table 4.3	Mean Samples to Decision for the Artificial Sensor Data Example	57
Table 5.1	Performance Characteristics for Calibration Verification	70
Table 5.2	Membership Functions for Performance Characteristics	74
Table 6.1	Sensor Statistics for the Artificial Data.	82
Table 6.2	Sensor Statistics for the Neutron Power Range Monitors.	83
Table 6.3	Summary of Test Cases for the ICVS.	93
Table 6.4	ICVS Input Parameters for the All Test Cases.	95
Table 6.5	ICVS Summary Results for Case I.	99
Table 6.6	ICVS Summary for Case II.	106
Table 6.7	ICVS Summary for Case III.	116
Table 6.8	ICVS Summary for Case V.	129
Table 6.9	ICVS Summary for Case V Using a +2% Bias for Sensors NPRM-1 and NPRM-2.	130
Table 6.10	ICVS Summary for Case VI.	132
Table 6.11	ICVS Summary for Case VII.	134

1. INTRODUCTION

1.1 Motivation for this Study

In nuclear power plants, redundant sensors are provided to monitor critical process variables for use in control, protection, and surveillance systems. Regulatory requirements and good engineering practice dictate that these sensors and their associated instrument channels be calibrated periodically to ensure a high confidence in their accuracy. Calibration of safety related sensors is normally performed on an annual cycle as outlined in the facility Technical Specifications. Operations personnel perform instrument checks once per shift to visually verify that redundant sensor outputs are consistent. The volume of sensor data to be verified and the subjectivity of the instrument check method make it difficult for the operator to verify the relative accuracy of an instrument channel, and to detect incipient changes in the sensor behavior over the time interval between calibrations. A non-intrusive method to verify that a sensor or a group of sensors is still in the calibrated state would aid personnel in making an assessment between calibrations. Additionally, the method would (1) base the frequency of calibrations on need rather than on the calendar, potentially leading to fewer calibrations and reduced radiation exposure to technicians, (2) allow more efficient outage planning, and (3) allow early identification of incipient calibration failures and chronic sensor problems.

Previous work directed specifically at calibration verification has focused on cross-checking of redundant instrumentation. Northeast Utilities was involved in the Instrument Calibration Reduction Program (ICRP) as early as 1986. The ICRP was initially concerned with the calibration frequencies of the core exit thermocouples (CET's). Analysis of variance (ANOVA) techniques were used to determine CET deviations from the mean of a group of CET's. Thermocouples which deviated excessively from the mean were excluded from the group average, while those whose deviations were within acceptable values were considered to be calibrated (at least, with respect to bias). Another program called the Redundant Instrument Monitoring System (RIMS) was implemented at San Onofre in 1988 [1]. RIMS continuously monitored redundant sensors and calculated a weighted average of sensors using the individual instrument accuracies. Again, the sensor deviations from the weighted average of a group of redundant sensors were flagged and tracked. More recently, an NRC funded program being carried out by Analysis and Measurement Services (AMS) Corporation performed a feasibility study of an on-line monitoring system using smart sensor technologies at Unit 2 of the McGuire Nuclear Power Station (1993).

The foundation of some of the above mentioned work was laid by basic research in signal validation techniques. Reference 2 presents the results of a comprehensive signal validation system that was completed at the University of Tennessee in 1989. The principle contributions of the signal validation techniques to this thesis are the consistency checking methodology, sequential probability ratio test, and the empirical modeling

algorithm. Earlier contributions in the area of sensor signal validation can be found in references 12 through 14.

The current project also takes advantage of available sensor redundancy to generate a process variable estimate. A consistency checking algorithm is used to provide a weighted estimate of the process variable using redundant signals [2]. The algorithm can identify and exclude an inconsistent signal under most circumstances. In addition, the algorithm will also generate performance indicators based on the degree of inconsistency of a sensor to the process variable estimate. Another test that is applied to the sensor data is a log likelihood ratio test called the sequential probability ratio test (SPRT). This test compares the current state of a particular sensor to the normal calibrated state for that sensor. Performance indicators are generated which quantify sensor deviations from the normal sensor state. These two methods can be used together to 1) generate an accurate estimate of the process variable, 2) verify that the total channel error for each redundant sensor is within the specified calibration tolerance, and 3) aid in predicting potential calibration drift errors over time.

1.2 Problem Statement and Overview of the Methodology

This research will provide a methodology to help verify the calibration state of redundant sensors. In particular, the methodology will determine if a sensor has experienced a bias drift, and will flag (although not explicitly quantify) changes in the

noise characteristics of a sensor that may affect it's calibration. The calibration state of a sensor is characterized by the deviation of a sensor from the process variable estimate. A sensor deviation that exceeds a given *tolerance* is considered to be unacceptable. The tolerance of a sensor is the maximum acceptable value that a sensor deviation may have, and may be derived from manufacturer's specifications or sensor measurements. Tolerances are not limited to physical sensor parameters (i.e., voltage, current, resistance) or to sensor units (e.g., temperature), but may be specified for any calculated parameter (e.g., mean square error of a set of sensor measurements).

The methodology proposed in the present work involves three fundamental tasks.

1) The determination of an estimate of the process variable.
2) Characterization of individual signal errors with respect to the process variable estimate for trend analysis, and to the calibrated state (as defined by the sensor tolerance) of the sensor derived from plant data.
3) Quantification of total estimate and signal inaccuracies for error bound and confidence estimation as input to the calibration verification process.

Process variable estimation is performed using the single variable consistency checking algorithm developed under the signal validation project at the University of Tennessee [2]. A process variable estimate is generated based on a weighted average of redundant signals. The weights are a function of the degree of consistency of a given signal to the other redundant signals. This estimate is taken to be the true value of the

process variable. A minimum of three redundant signals are required for proper application of this algorithm. This is supplemented by an algorithm that generates a non-linear polynomial model of the process variable estimate. The model acts as an additional redundant signal, and as an independent and functionally diverse verification of the process variable estimate.

The characterization of the individual sensor errors relative to the process variable estimate is performed in three ways. First, the mean deviation of a sensor from the process variable estimate is determined over the current sample space of the sensor. This characteristic deviation can be compared directly to the calibrated state of that sensor for acceptability, or to the previous sample spaces to detect trends. The standard deviation of the sensor over the current sample space will also be calculated to verify that the sensor noise characteristics have not changed. Next, the consistency checking algorithm is used to determine the degree of inconsistency of a sensor with the other redundant sensors, and the number of samples for which the signal is excluded from the process variable estimate. The degree of inconsistency provides a measure of agreement among redundant sensors. The number of exclusions indicates the percentage of time that a sensor is completely out of tolerance with redundant sensors. Finally, a cumulative log likelihood test will be applied to a sensor over the current sample space. The characteristics of this test provide an additional way of verifying the calibration state of a sensor, detecting trends over many sequential sample spaces, and detecting degraded behavior within a sample space.

To verify the calibration state of a sensor the total cumulative error must be quantified for the process variable estimate and for the individual sensor signals. An error bound, and its associated confidence, are determined for each sensor and the process variable estimate. If the calculated error bound is within tolerance limits, and its confidence is high, then the sensor is inferred to be calibrated. However, if the error bounds exceed the acceptable tolerance, then a problem exists with the calibration of the sensor, and the sensor is declared to be out of tolerance. In either case, if the confidence is below acceptable limits, then the degree of belief in the results is questionable, and the test is declared inconclusive.

These methodologies can be applied to any type of sensor that has an adequate level of redundancy. The operating principle of a sensor is not a factor in applying the algorithms. However, the non-linear polynomial model of the process variable estimate requires some consideration. The process variables that are chosen to generate a model must have a physical relationship to each other and must have enough sensitivity to be effective parameters in the model under the expected conditions of the process. For example, the power range neutron monitors and hot leg temperature are closely linked, while the link with the steam generator level is weaker (due to the level control system). Therefore changes in the hot leg temperature would have a greater effect than the steam generator level on the predicted response for the neutron monitors.

1.3 Contributions of the Thesis

Previous work in calibration reduction programs has focused on the cross checking of redundant sensors with each other, and with a known calibrated sensor. A process variable estimate is generated using a weighted average (the weighting factors are based on individual sensor accuracies), and the individual sensor deviations are compared to this estimate. In this work, a process variable estimate is also generated using a weighted estimate, but the weighting factors used are based on the degree of consistency of the individual sensors, thus allowing partial inconsistences to contribute to the estimate on a sample by sample basis. A concept from fuzzy set theory called a fuzzy membership function is used to scale the weighting factors. Further, an empirical model is used to generate an analytical estimate of the process variable. This estimate provides an additional point of redundancy, and a check against certain types of common mode failures that may occur within a group of redundant sensors. Another new application is the use of the sequential probability ratio test (SPRT) to check the normal vs. faulted state of individual sensors. The SPRT provides a diverse means of verifying that a sensor has not deviated from it's normal state. Finally, fuzzy membership functions are used as an aid in the determination of the calibration state of the sensors.

1.4 Organization of the Thesis

This thesis is divided into seven chapters. A brief discussion of the regulatory

requirements and codes and standards that help define the motivation and requirements for instrument calibration are presented in Chapter 2. The estimation of process variables using redundant and functionally diverse sensors is discussed in Chapter 3. An evaluation of the error bounds and confidence of the process variable estimates is also presented. Chapter 4 discusses the quantification of sensor deviations from the process variable estimate in terms of calculated parameters derived from sensor statistics, generalized consistency checking test, and the sequential probability ratio test. In Chapter 5, the method for determining signal tolerance is defined. Sensor deviations from the process variable estimate are evaluated for acceptability in terms of fuzzy membership functions. Chapter 6 presents the application of the methodology to a sample of steady-state data obtained from an operating pressurized water reactor. Seven test cases are examined to determine the effects of different combinations of calibration drift. Finally, Chapter 7 provides a summary, and a discussion of the conclusions of the thesis and recommendations for future work.

2. CALIBRATION REQUIREMENTS

2.1 Regulatory Requirements

The fundamental requirements for the surveillance and testing of nuclear power plant instrumentation are stated in Appendix A of 10CFR50, "General Design Criteria for Nuclear Power Plants" [3]. Of particular interest with regard to instrument calibration are General Design Criteria 13 and 21. The following is paraphrased from Regulatory Guide 1.153, "Criteria for Power, Instrumentation, and Control Portions of Safety Related Systems" [4]:

* Criterion 13, "Instrumentation and Control", requires that instrumentation be provided to monitor variables and systems over their anticipated ranges for normal operation, anticipated operational occurrences, and accidents to assure adequate safety and requires appropriate controls to maintain variables and systems within prescribed operating ranges.

* Criterion 21, "Protection System Reliability and Testability", requires the protection system to be designed with high functional reliability and inservice testability. This criterion also requires redundancy and independence to provide protection against single failures and retention of redundancy (except where justified) in the event equipment is removed from service. On-line testing is required. (Underling added by author)

Criterion 13 is the fundamental design criterion which requires instrumentation to monitor and control system process variables over normal and accident conditions. Criterion 21 requires a program of inservice testing of the instrumentation and control systems,

including the ability to perform on-line testing. The regulatory position for meeting these requirements is outlined by Regulatory Guide 1.153, which dictates conformance to ANSI/IEEE Standard 603-1980 [5] for plants with construction permits docketed on or after November, 1985, or IEEE Standard 279-1971 [6] for plants with construction permits docketed before November, 1985.

2.2 Codes and Standards

As discussed above, nuclear plants are obligated to conform to ANSI/IEEE Standard 603-1980, "IEEE Standard Criteria for Safety Systems for Nuclear Power Generating Stations", or IEEE Standard 279-1971, "Criteria for Protection Systems for Nuclear Power Generating Systems", depending upon their construction permit date. Although the standard 279-1971 applies to protection systems only, both standards address requirements for testing and calibration of safety related instrumentation. Section 6 of standard 603-1980 outlines the functional design requirements of the sense and command features (i.e. protection systems) of safety related systems. In particular, paragraph 6.5.1 states:

> Means shall be provided for checking, with a high degree of confidence, the operational availability of each sense and command feature input sensor required for a safety function during operation. This may be accomplished in various ways, for example, (1) by perturbing the monitored variable, (2) within the constraints of 6.6 (operating bypasses), by introducing and varying, as appropriate, a substitute input to the sensor of the same nature as the measured variable, or (3) by cross-checking between channels that bear a known relationship to each other and that have readouts available.

Normal channel calibration methods used at nuclear power plants apply combinations of all three of the above suggested approaches. Checks are performed at different operating conditions to verify accuracy over the span of the sensor. Test signals are injected into an instrument channel to verify the responses of readouts, setpoints, and other logic. Cross calibrations are performed to verify consistency between redundant or diverse instrumentation (e.g. core exit thermocouples and loop RTDs). Between calibrations, operations personnel will perform qualitative "instrument checks" to verify that redundant instruments are providing reasonable output.

2.3 Instrument Tolerances

To understand the basis for the allowable tolerances of safety related instrumentation, one must understand the design criteria for process variable operating limits, and the safety related systems designed to maintain these limits. For every commercial nuclear power plant, there is a set of accident analyses that is performed to determine the response of the plant to various transients ranging from a turbine trip to a full double-ended rupture of a main coolant loop. These analyses form the basis of what is considered to be safety related in a nuclear power plant, and are outlined in the plant's Final Safety Analysis Report (FSAR). The accident analyses determine the bounds in which a nuclear plant may safely operate for various modes of operation. The bounds include what equipment must be operable, process variable limits (pressure, temperature, flow), instrument setpoints, and operating constraints such as power ramp and cooldown

rates. These bounds are implemented through the plant Technical Specifications, and include the Limiting Conditions for Operations (LCOs) which define the operating constraints (i.e. power level, pressure etc.) for various states of equipment availability.

In determining the setpoints of the protection system, assumptions are made concerning the instrument errors due to the calibration process itself, instrument zero and range drift, and overall channel accuracy (including the accuracy of transmitters, indicators, etc.). Each of these factors can introduce errors into the measurements taken by an instrument channel. Figure 2.1 illustrates a typical relationship between instrument setpoints and process variable safety limits. For this example, variables X and Y are process variables that define the state of the system (e.g., pressure and temperature). Line 1 represents a functional boundary between the unacceptable and acceptable

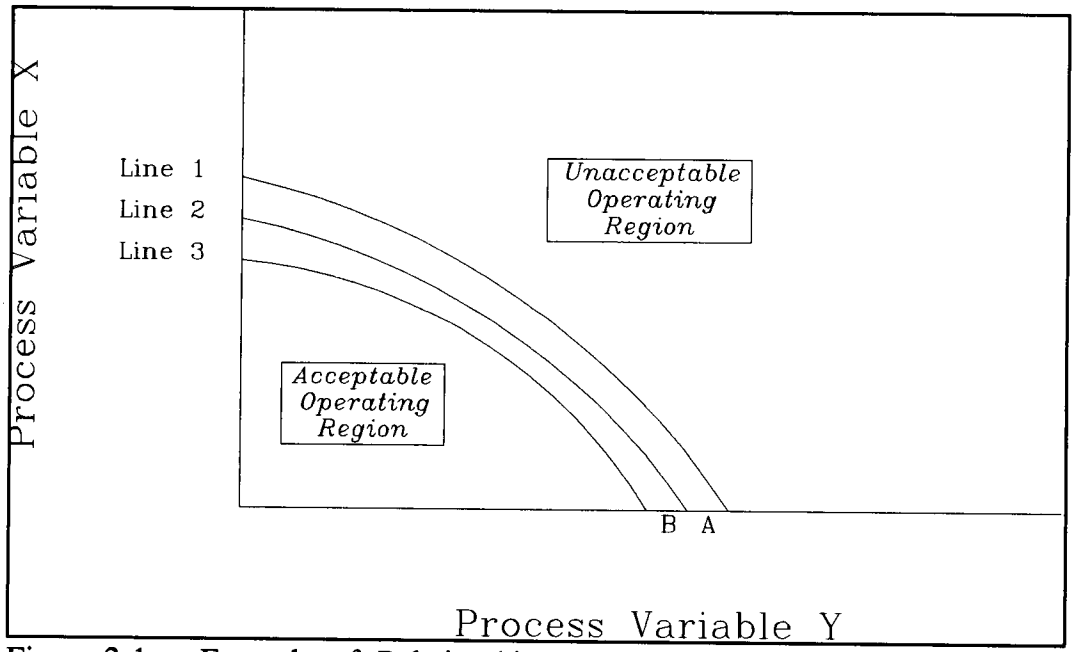


Figure 2.1 Example of Relationship Between Nominal Protection System Setpoints and Limits of Safe Conditions. (reference [5])

operating regions for the process variables X and Y. This boundary is based upon the accident analysis results for a given set of postulated transients or accidents. Line 2 is formed as a practical limit for protection system setpoints to account for errors during calibration, channel accuracy, and transient overshoot (i.e., the degree which a process variable setpoint is exceeded due to the speed of the transient and the response time of the instrument channel and any actuated equipment). The gap labeled A represents these errors. Further uncertainties associated with instrument and setpoint drifts (gap B) result in line 3, the target line to which calibrations are performed. Paragraph 4.4.4 of standard 603-1980 requires that the assumed increment (gap B) between the setpoint allowable value (line 2) and the trip setpoint (line 3) be demonstrated as an acceptable and reasonable value to accommodate zero and range drift during the interval between calibration verification tests. Thus the instrument tolerance for a given channel must at a minimum include the errors represented by gap A and gap B. In practice, the tolerances used for calibration will exceed these errors by some factor of safety.

3. PROCESS VARIABLE ESTIMATION

3.1 Introduction

In attempting to ascertain the calibration state of a sensor, it is necessary to determine the expected value of the process variable. This can be used to analyze sensor deviations from the true value of the process variable over time. In practice, the expected value of the process variable can be taken to be the true value, provided that the uncertainties are small compared to the specified tolerance for a given sensor.

There are several *estimators* which can be applied to yield the expected value of a process variable, the simplest of which is the mean of the sensor output. This method, however, has a large uncertainty since it depends upon a single sensor, and errors in that sensor may yield significant inaccuracies in the expected value of the process variable. An improvement in the estimate uncertainty can be obtained by determining the mean of a group of redundant sensors, such as those found in nuclear power plants. This helps to insulate the estimation from an individual sensor anomaly by averaging with other sensors with presumably normal responses. For this method to yield an accurate estimate, the sensors must be truly redundant (i.e. be spatially close or continuous), and an individual sensor's error must be relatively small, or large enough to be easily identified as faulty and discarded from the estimate. A signal with an intermediate bias can result in a large undetected error in the process variable estimate. Finally, this

method does not preclude the possibility of a common mode failure that can cause all redundant sensors to experience the same kind of deviation. A typical example of this is a set of redundant sensors, all of which are calibrated with the same instrument (such as a digital multimeter), that experience roughly the same bias error if the calibration instrument itself is not properly calibrated.

In the present work, two methods are used to estimate the true value of the process variable. The generalized consistency checking (GCC) and the process empirical modeling (PEM) algorithms were developed under the Signal Validation Project at the University of Tennessee [2]. The GCC method applies a complex logic that will assign weights to each redundant signal depending upon the relative consistency between each pair of sensors. In the extreme case, it will eliminate a signal from the process variable estimate if that signal is totally inconsistent with the other sensors. The PEM method involves a set of data driven multiple-input single-output models that are created from the plant data. This algorithm will generate an independent estimate of a process variable based upon diverse variables that are physically related in a specified plant system. Therefore, common cause failures of the redundant sensors of interest should yield inconsistencies between each of the measured values and the PEM generated estimate.

3.2 Generalized Consistency Checking

The GCC algorithm compares the difference between a pair of sensors for a given sample against a specified maximum acceptable deviation. A pair of sensors is consistent if

$$|m_i - m_j| \leq b_i + b_j \tag{3.1}$$

where m_i and m_j are measurements of the ith and jth sensor for a given sample, and b_i and b_j are their specified tolerances. The selection of b_i and b_j is based upon either 1) the instrument vendor specifications or, 2) the distribution of the sensor measurements when the sensor is known to be calibrated. This will be discussed in more detail in section 5.3. If the above relation is false, we define a *cumulative inconsistency index* C_i and C_j such that

$$if \quad |m_i - m_j| > b_i + b_j \ , \quad then \quad \begin{cases} C_i = C_i + 1 \\ C_j = C_j + 1 \end{cases} \tag{3.2}$$

where C_i and C_j are initially set to zero for each new sample. This criterion is applied to each pair of sensors, with each sensor's cumulative inconsistency index incremented by one if the pair does not meet the criterion. For N redundant sensors, the maximum cumulative inconsistency index possible is N-1. If a particular sensor has a cumulative

inconsistency index equal to the maximum possible value, then it is declared completely inconsistent, and is excluded from the process variable estimation for the current sample. The GCC algorithm is then reapplied to the remaining sensors, and a new set of cumulative inconsistency indices are generated. If a sensor has a cumulative inconsistency index less than the maximum possible, then it is declared partially consistent, and is used in the process variable estimate with a weight based on the value of its inconsistency index. The process is repeated for the next sample, with all sensors initially included.

As an example, consider a set of four artificial sensor measurements represented by the density functions in Figure 3.1. The measurements are intended to represent the steady-state condition of a process variable "Y". They exhibit Gaussian distributions with mean values of 99.7, 99.9, 100.1, and 100.3 units, and standard deviations of 0.2 units. Applying the GCC algorithm with a specified tolerance of ±1 unit, allsensors are consistent for all samples, and therefore $C_i = 0$ for all sensors at all samples. If a one unit bias is added to sensor #4 as shown in Figure 3.2, then the value of C_i may be non-zero for all sensors as inconsistencies occur throughout the sample space. Figure 3.3 illustrates the behavior of the cumulative inconsistency index for the four sensors in this example. As can be seen from the figure, the faulted sensor (#4) has more inconsistencies than the other three sensors, including several instances where it was inconsistent with more than one sensor (i.e., C_4 is equal to 2). Sensor #4 would therefore have a lower overall weight in the estimation process.

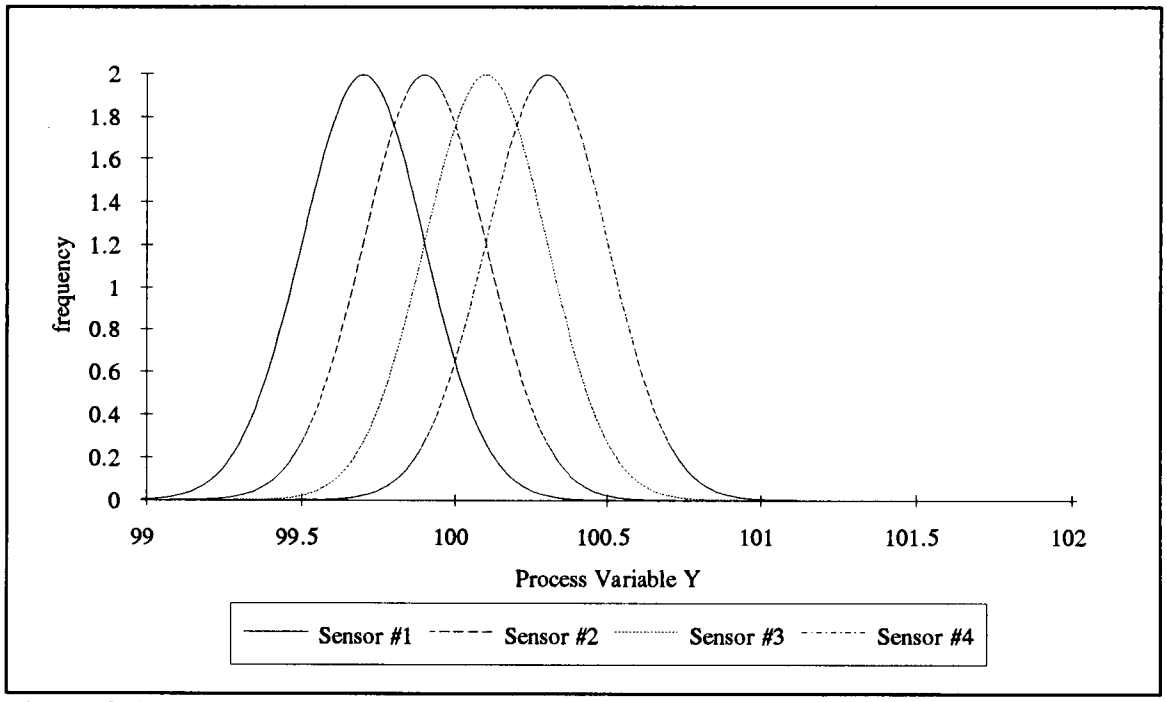


Figure 3.1 Example Density Functions of Four Normal Redundant Sensors

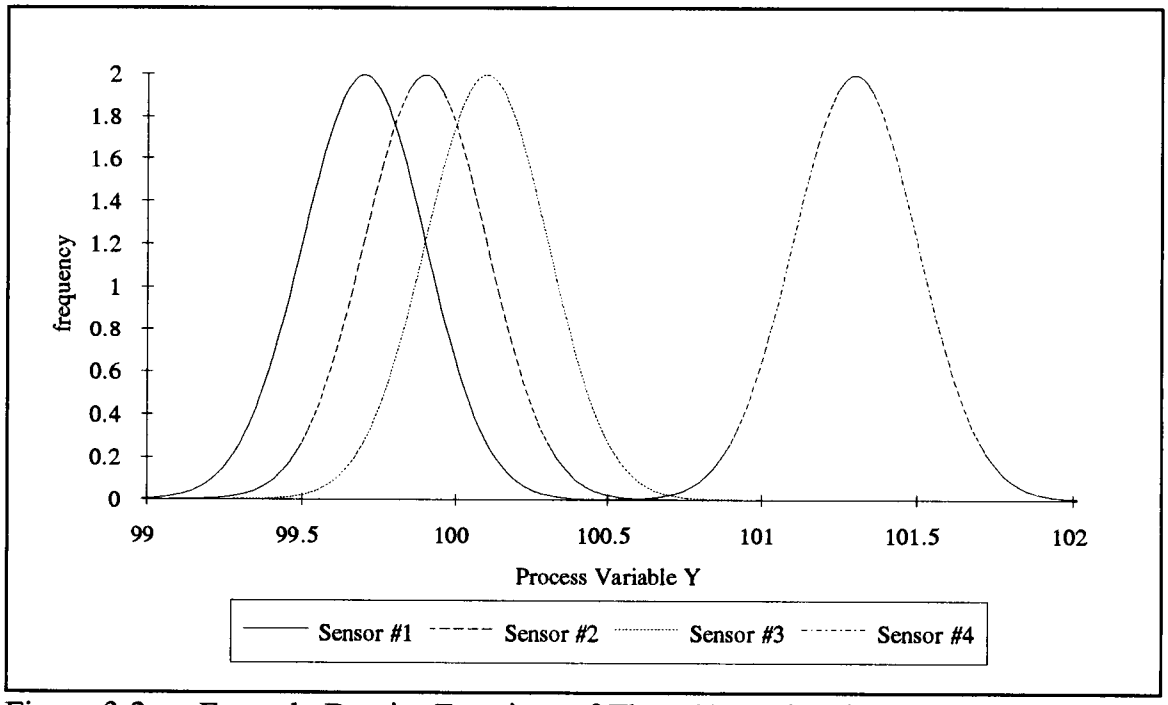


Figure 3.2 Example Density Functions of Three Normal and One Degraded Sensor

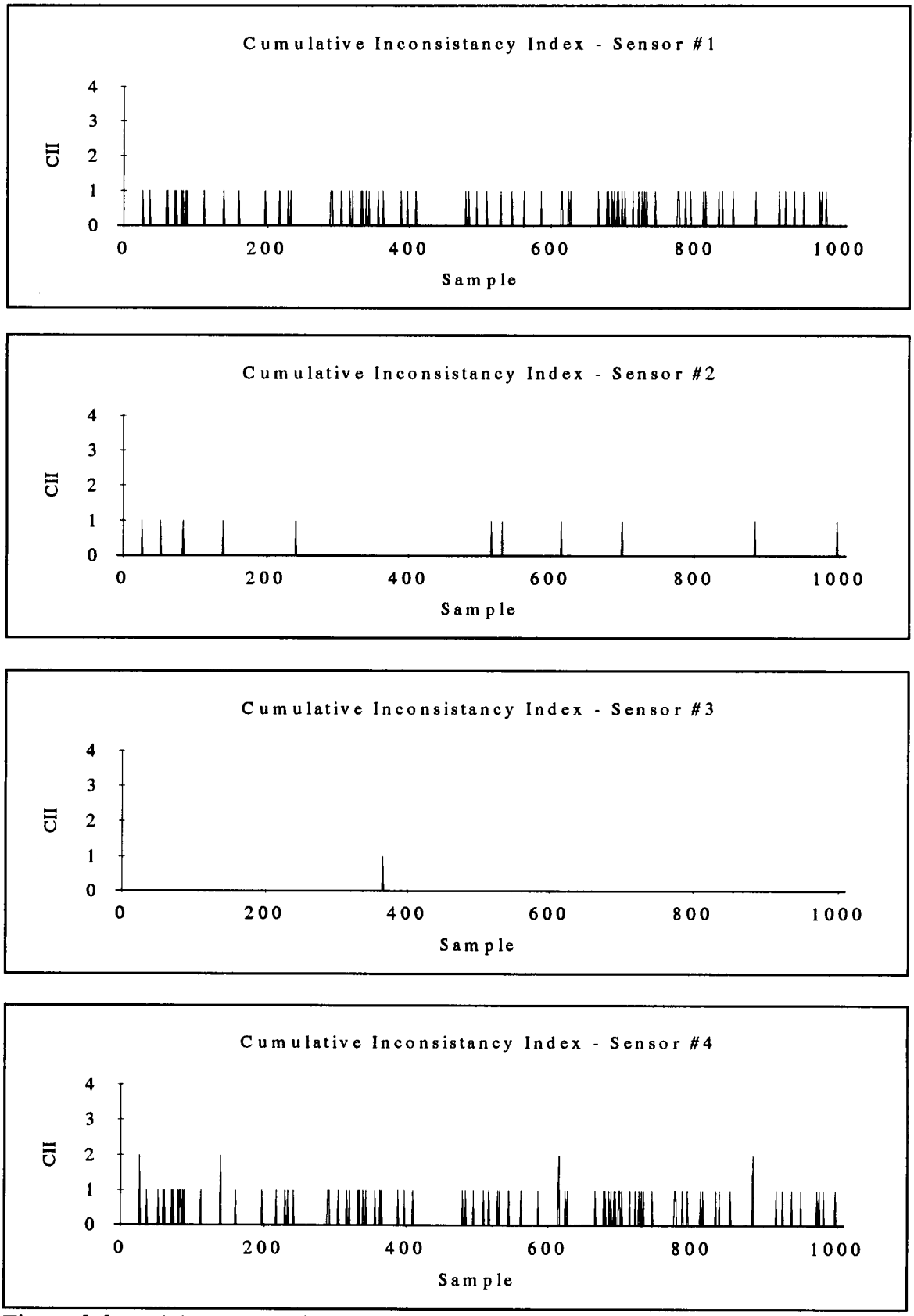


Figure 3.3 GCC Cumulative Inconsistency Indices - Example 1

The GCC algorithm estimates the process variable using a weighted average of redundant sensors, with a weighing function, w_i, based on the sensor cumulative inconsistency indices.

$$Y_{GCC} = \frac{\sum_{i=1}^{N} w_i m_i}{\sum_{i=1}^{N} w_i} \tag{3.3}$$

Although the choice of w_i is somewhat arbitrary, it should be a monotonically decreasing function of increasing error. For example, the form of w_i in an earlier application of the GCC algorithm [2] used a linear function,

$$w_i = N-1-C_i \tag{3.4}$$

where N is the total number of signals and C_i is the cumulative inconsistency index of sensor i. This generates a weight which is proportional to the inconsistency index of signal i. Another useful form of w_i can be derived using the fuzzy set z-curve membership function

$$w_i = \begin{cases} 1 - \frac{2}{\beta^2} C_i^2 & for\ 0 \le C_i \le \frac{\beta}{2} \\ \frac{2}{\beta^2} (C_i - \beta)^2 & for\ \frac{\beta}{2} \le C_i \le \beta \end{cases} \tag{3.5}$$

where β is the *bandwidth* of the z-curve. The bandwidth is equal to the range of the z-curve. In this application β is equal to N-1. A plot of this curve is shown in Figure 3.4. This weighing function places greater emphasis on signals that have zero or one inconsistencies. The resulting signal estimate is then less sensitive to signals with greater errors. The fuzzy membership function presented here is described in greater detail in Section 5.2.

Certain conditions must be met for the GCC algorithm to generate a process variable estimate. For N signals available, no more than N-2 signals can have a maximum cumulative inconsistency index. That is, if more than N-2 signals have a maximum inconsistency index, then all signals will be declared inconsistent, and the algorithm will not generate an estimate. In such a case, the previous value of the estimate (if it exists) is passed as the current value.

An example of a GCC estimate vs. measurements is shown in Figure 3.5. The process variable is reactor power measured using four nuclear power range monitors. All of the sensors are normal, and are used to generate the GCC estimate. The input data and GCC results are described in more detail in Chapter 6.

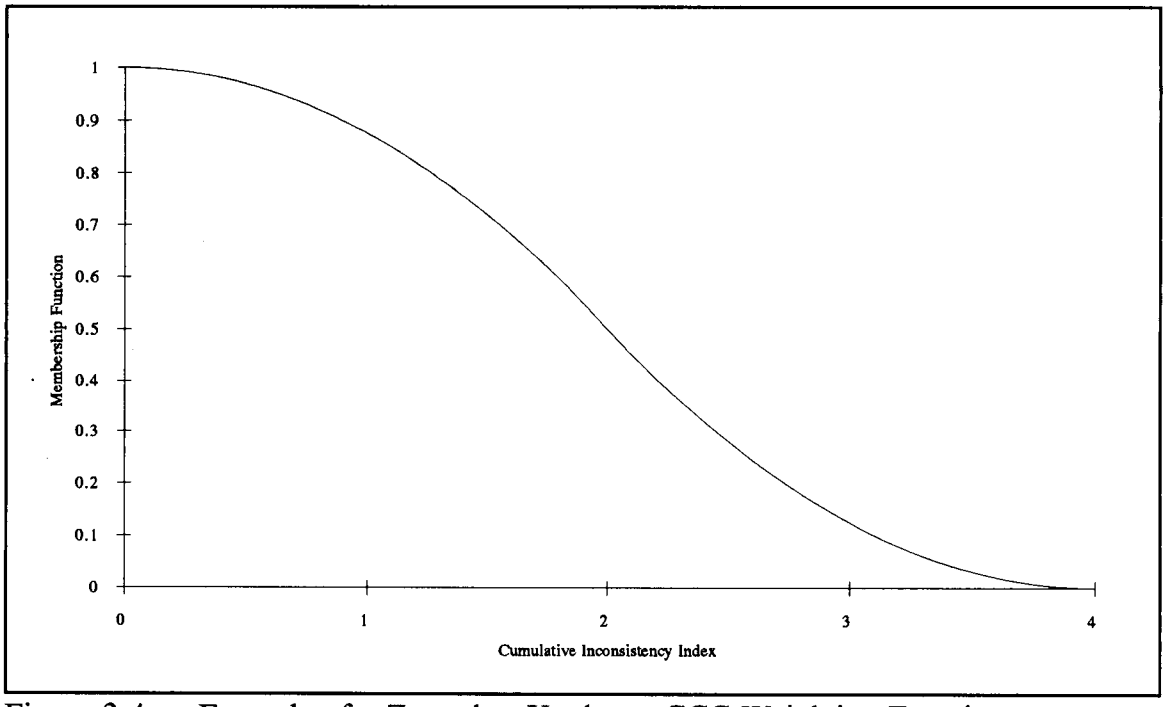


Figure 3.4 Example of a Z-number Used as a GCC Weighting Function

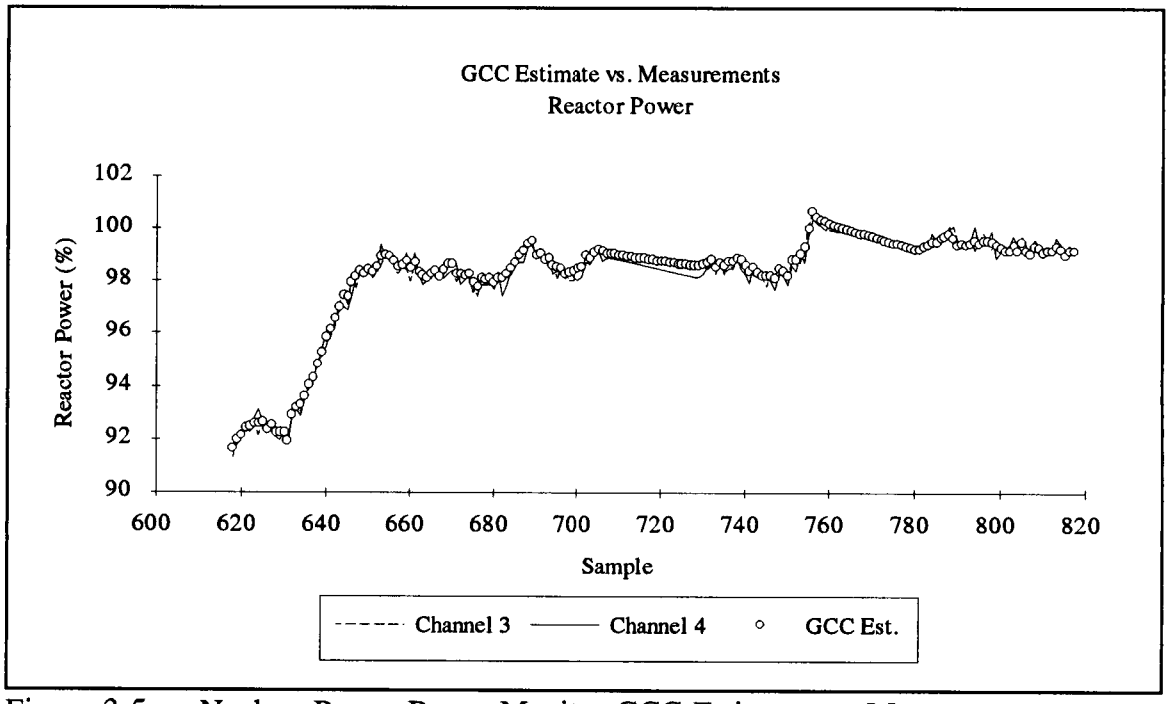


Figure 3.5 Nuclear Power Range Monitor GCC Estimate vs. Measurement

The fundamental advantage of the GCC method over standard statistical estimation is its ability to identify partial or complete inconsistencies among redundant sensors, and to assign an appropriate weight to each of the signals used in the process variable estimation. This reduces the effect of samples from sensors that are out of tolerance, and thus provides a more accurate process variable estimate. In addition, the GCC algorithm will provide a measure of a sensor's performance, and the estimate will be used as an input to the Sequential Probability Ratio Test (SPRT), as discussed in Section 4.4.

3.3 Process Empirical Modeling

The nonlinear modeling algorithm developed for the Signal Validation Project is based on a method of nonlinear polynomial fitting by Desrochers and Mohseni [7]. A detailed description of this algorithm is beyond the scope of the present work, but can be found in [2]. The general form of the nonlinear model is given by

$$Y_{PEM} = A_o + \sum_{i=1}^{n} A_i \phi_i (X) \tag{3.6}$$

where Y_{PEM} is the estimate of the output variable, $X = \{x_1, x_2, \ldots, x_m\}$ is the set of input variables that affect the behavior of Y, and $\{A_0, A_1, \ldots, A_n\}$ is a set of constant coefficients. Nonlinear or cross product functions of X are given by the terms $\{\phi_1, \phi_2, \ldots, \phi_n\}$. The procedure that generates the model sets up a vector space V(i) which

consists of n vectors (where n is the number of possible cross products) of dimension L (where L is the number of steady-state measurements of Y and X)

$$V(i) = \{\phi_i(X(k))\} \tag{3.7}$$

where i = 1,2,...,n and k = 1,2,...,L . In this space, the output variable (the estimated variable) is represented as a 1 x L vector. The objective is to select p terms, p < n, to give an optimal fit similar to the least-squares procedure. To limit the complexity of the calculation, the maximum number of terms and the maximum order of the model can be specified. After the cross product terms $\{\phi_1,\phi_2,\ldots,\phi_n\}$ are calculated, the coefficients $\{A_0,A_1,\ldots,A_n\}$ are determined using the least-squares method.

The PEM algorithm produces a multiple input single output (MISO) model of the relationship between process variables that characterize a plant system. The models created by PEM typically use three to four process variables as inputs, and one desired output process variable as shown in Figure 3.6. For example, the output of the power range neutron monitors for a reactor can be empirically modeled by using the measured signals for hot and cold leg temperatures, pressurizer level, and main steam pressure. A more accurate model prediction can be obtained by using validated estimates of the input variables (such as can be produced by the GCC algorithm) to reduce the possibility of a faulty input sensor adversely affecting the empirical model output. An example of

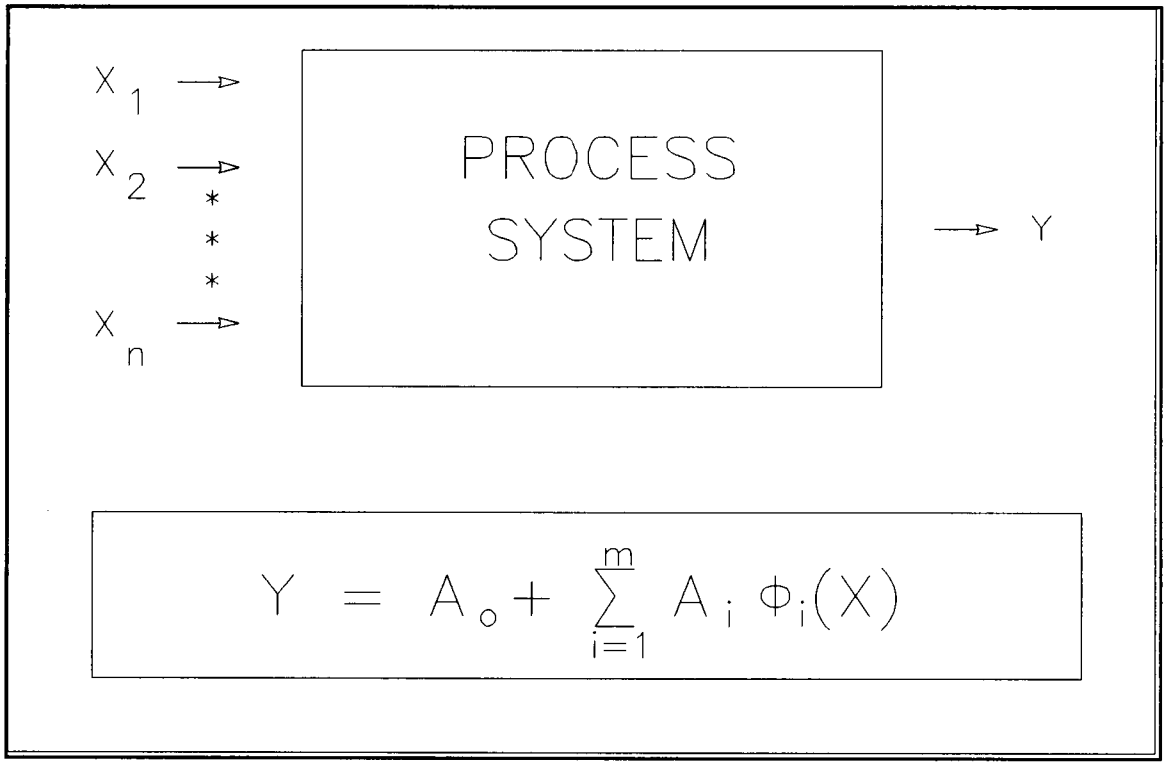


Figure 3.6 Input/Output Relationship in a PEM Model

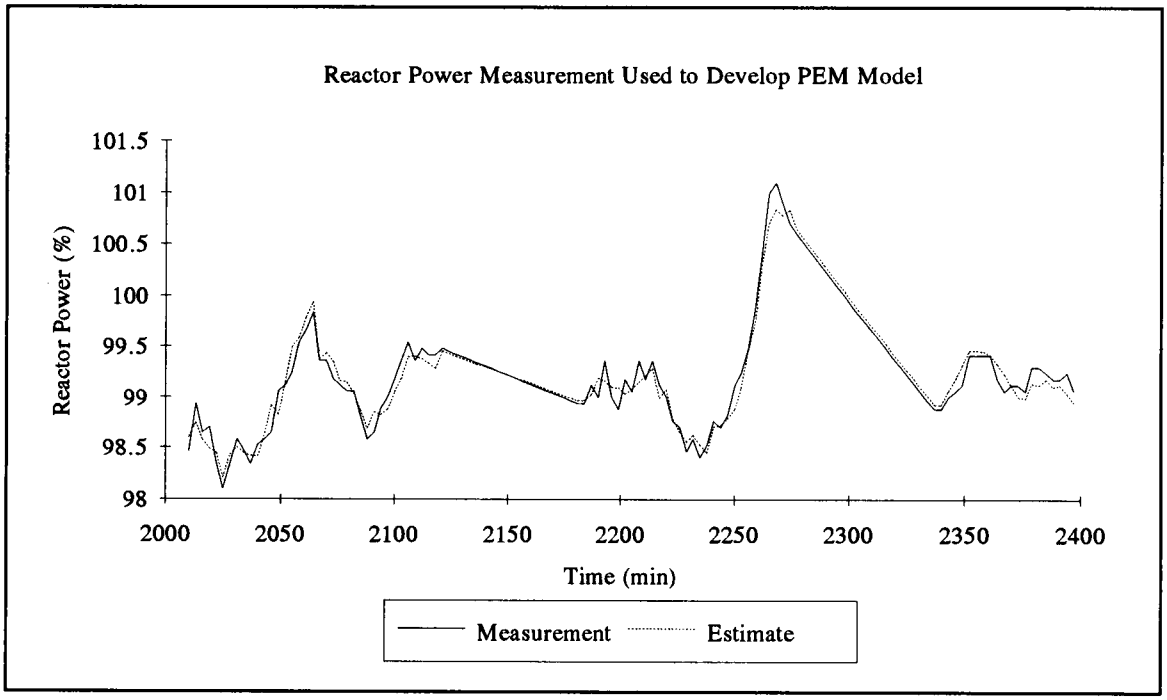


Figure 3.7 PEM Estimate vs. Reactor Power Measurements.

a PEM model estimate over a 3% range of reactor power is shown in Figure 3.7.

The results from the PEM model for the process variable of interest will be used as 1) an independent and diverse estimate of the process variable, which can provide a cross check on the GCC estimate, and 2) an additional point of redundancy for input into the GCC algorithm. An inconsistency occurring between the PEM estimate and the GCC estimate may be an indication of a common cause error among the redundant signals used by the GCC algorithm.

3.4 Evaluation of the Error Bound of Process Variable Estimates

An important facet in determining the adequacy of an instrument's calibration state is assigning an uncertainty to the process variable estimate. The more accurately we can estimate the true value of the process variable, the greater is the confidence in the calibration state of a sensor. *Error bounds* can be determined for each sensor, and appropriate methods derived to determine if the measured and estimated values are within acceptable limits of each other. The *confidence* in the estimate of the process variable is the degree of belief, or probability, that the true value lies within the error bounds determined. The determination of error bounds for a specified confidence may be based on considerations discussed in Section 2.3, or upon the historical normal behavior of a given sensor.

3.4.1 Uncertainty of the Generalized Consistency Checking Estimate

In determining the uncertainty associated with an estimate generated by a set of redundant sensors, we must determine a method of combining the uncertainty of the individual sensors. This will allow us to take advantage of the available redundancy to obtain a smaller error bound at a specified confidence (or a greater confidence for a specified error bound) than is possible with a single sensor. Ultimately, our goal is to quantify the error bound and confidence of the *estimator* that we use to predict the process variable Y.

Using a single normal sensor, we can measure the process variable Y, and determine an error bound based upon the signal distribution. For example, a sensor whose signal exhibits a Gaussian distribution could be assigned an error bound of $\pm 2\sigma$, with an associated confidence of 0.95. We can use the mean of the sensor measurements μ, to represent the true value of the process variable Y, and assign an error bound of $\pm e$, where $e = 2\sigma$. For a Gaussian distribution, the confidence associated with this error bound is prescribed by the following relationship

$$P(-2\sigma \le Y \le +2\sigma) = \int_{-2\sigma}^{+2\sigma} \frac{\exp\{-(y-\mu)^2/2\sigma^2\}}{\sigma\sqrt{2\pi}}\, dy \approx 0.95 \qquad (3.8)$$

Now assuming that we have two such sensors with similar characteristics, we may

make two redundant measurements y_1 and y_2 of the process variable Y, each with individual uncertainties of e_1 and e_2. If the two sensors behave normally, then it will be possible to construct two probability density functions, with mean values of μ_1 and μ_2. Note that the two sensors are not statistically independent, since they are measuring the same process variable. However, the *distribution* of measurements around the mean value of each sensor (i.e., the sensor deviations from the mean) can be treated as an independent random variable. This can be verified by demonstrating that the covariance of the sensor deviations is approximately zero.

$$Cov(Y_1, Y_2) = E[(Y_1-\mu_1)(Y_2-\mu_2)] \simeq 0 \tag{3.9}$$

For this case, we can construct an estimator Y_{mean} which is the mean of both sensor measurements over the sample space S;

$$Y_{mean} = \frac{1}{S}\sum_{i=1}^{S}\frac{(y_{1i}+y_{2i})}{2} = \frac{1}{2}(\mu_1+\mu_2) \tag{3.10}$$

The estimator Y_{mean} is a function of the random variables Y_1 and Y_2, and therefore is also a random variable. If Y_{mean} exhibits a Gaussian distribution with a standard deviation σ, then the error bound and confidence of the estimator can be taken to be $e = 2\sigma$ and 0.95, respectively. If the distribution is not Gaussian, the error bound and confidence can be determined using numerical integration of the frequency histogram of the data. To see

how well the estimator fits a Gaussian distribution, we can calculate the *coefficient of skewness* and the *coefficient of kurtosis* of the estimator data. The skewness of a distribution is a measure of its symmetry. Values of skewness less than zero indicate a longer tail to the "left" of the mean, while values greater than zero indicate a longer tail to the "right" of the mean. The coefficient of skewness is defined by the following relation.

$$\beta_3 = \frac{1}{N\sigma^3} \sum_{i=1}^{N} (y_i - \mu)^3 \tag{3.11}$$

The coefficient of kurtosis gives an indication of the flatness (relative to a Gaussian shape) of a distribution. Values of the kurtosis greater than one indicate a more central concentration of data, while values less than one indicate a broader distribution of data. The coefficient of kurtosis is given by the following relation.

$$\beta_4 = \frac{1}{3N\sigma^4} \sum_{i=1}^{N} (y_i - \mu)^4 \tag{3.12}$$

Test results from data that do not conform well to the assumed Gaussian distribution may not be valid.

As an example, refer to the frequency histograms plotted in Figure 3.8. The data was randomly generated to exhibit a Gaussian distribution. The means of the two sensors are 99.7 and 100.3 units, and the standard deviation for both sensors is 0.2 units. Also plotted in Figure 3.8 is the histogram of Y_{mean}. The mean and standard deviation of Y_{mean} is 100.0 and 0.14 units respectively. Thus, by using two normal redundant sensors, we have improved our error bound for a given confidence.

A major drawback of this type of estimator is the inability to detect degraded sensors. If one of the sensors is degraded, it will severely bias the estimate, and the error bound will remain relatively unaffected. This may lead to a false conclusion regarding the value of the process variable. For example, Figure 3.9 shows sensor #1, #2, and Y_{mean} with a one unit bias applied to sensor #2. In this case, the mean of Y_{mean} has shifted to 100.5, while the standard deviation remains at 0.14. Thus the estimate would appear to be accurate, while in fact it is biased by 0.5 units. Furthermore, it may not be possible to determine which sensor is degraded, even if there are additional sensors available. In this case, the estimate of the process variable is inconclusive for the verification of the calibration state of a sensor. Finally, this method cannot detect a *common cause* failure of the two sensors. A common cause failure could result in a severely biased estimator that may not be detectable. The GCC algorithm can improve the accuracy of the estimate (when three or more sensors are used) by excluding from the estimate those measurements that do not meet the specified tolerance criterion. Since Y_{GCC} is a function of random variables (see (3.2)), it is also a random variable.

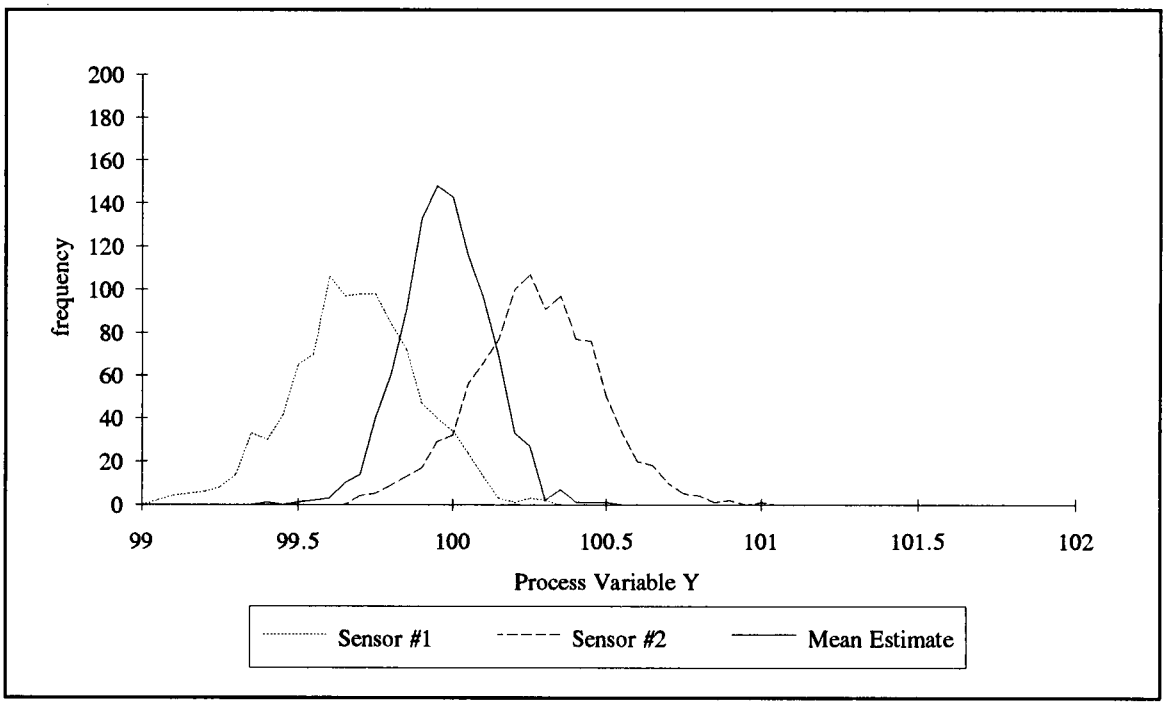


Figure 3.8 Example of a Mean Estimator Using Two Normal Sensors.

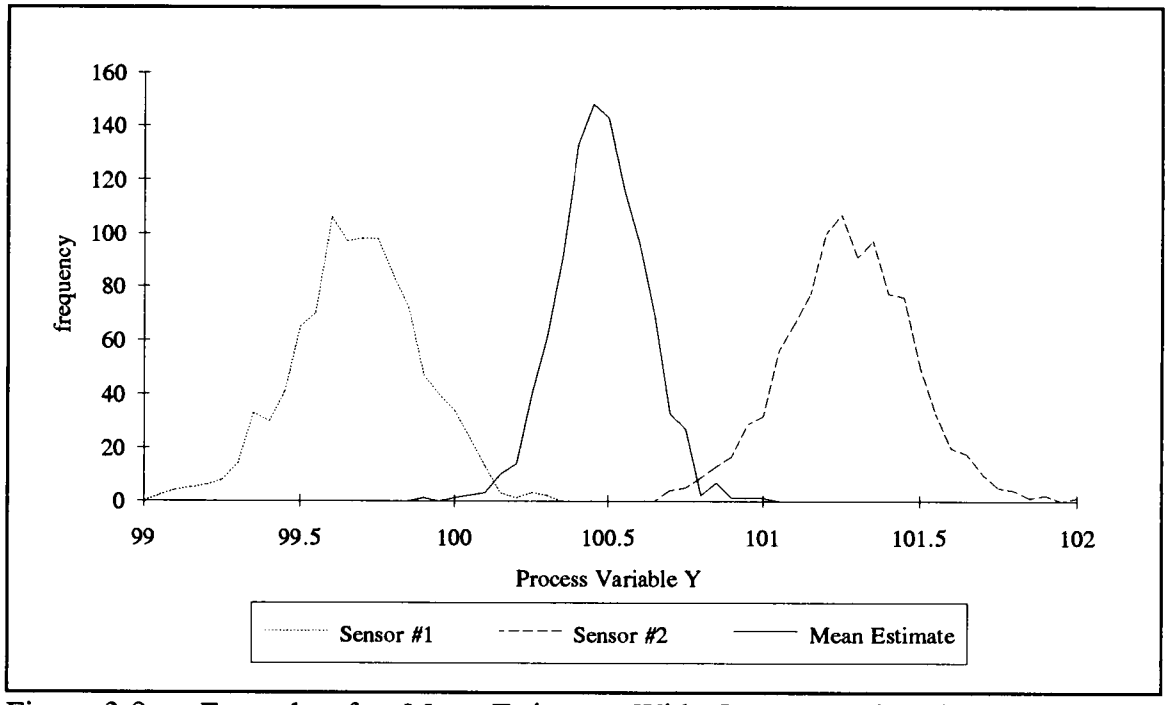


Figure 3.9 Example of a Mean Estimator With One Normal and One Degraded Sensor.

The relationship between the error bound and the confidence is given by:

$$confidence = P(-\varepsilon \le Y \le +\varepsilon) = \int_{-\varepsilon}^{+\varepsilon} p(y)\, dy \qquad (3.13)$$

where ε is the prescribed error bound and *p(y)* is the probability density function of Y_{GCC}. In practice, the confidence for a given error bound can be determined by numerical integration of the frequency histogram of Y_{GCC}, or by using the *percentile* of the data for Y_{GCC}. As an example of multiple sensors, let us examine the case of four sensors as shown in Figure 3.10. For this example, the true value of the process variable is taken to be equal to 100.0. Sensors #1, #2, and #3 have mean values of 99.7, 99.9, and 100.1 units respectively. Sensor #4 is faulted, and has a mean of 101.3 units. All four sensors have standard deviations equal to 0.2 units. Estimates of the process variable were calculated using Y_{mean} and Y_{GCC}, and their distributions are compared in Figure 3.11. A tolerance of 0.6 units (3 standard deviations) was specified for the GCC algorithm.

The mean values of Y_{mean} and Y_{GCC} are 100.25 and 100.01 units, and the standard deviations are 0.10 and 0.18 units, respectively. Thus Y_{GCC} provides a better estimate than Y_{mean} of the true value of the process variable. As can be seen in Figure 3.11, the distribution of the GCC estimate is skewed to the right. This is due to the effect of measurements from sensor #4 that were not excluded from the estimate. Since the distribution is distorted from a Gaussian distribution (the skew and kurtosis equal 0.13

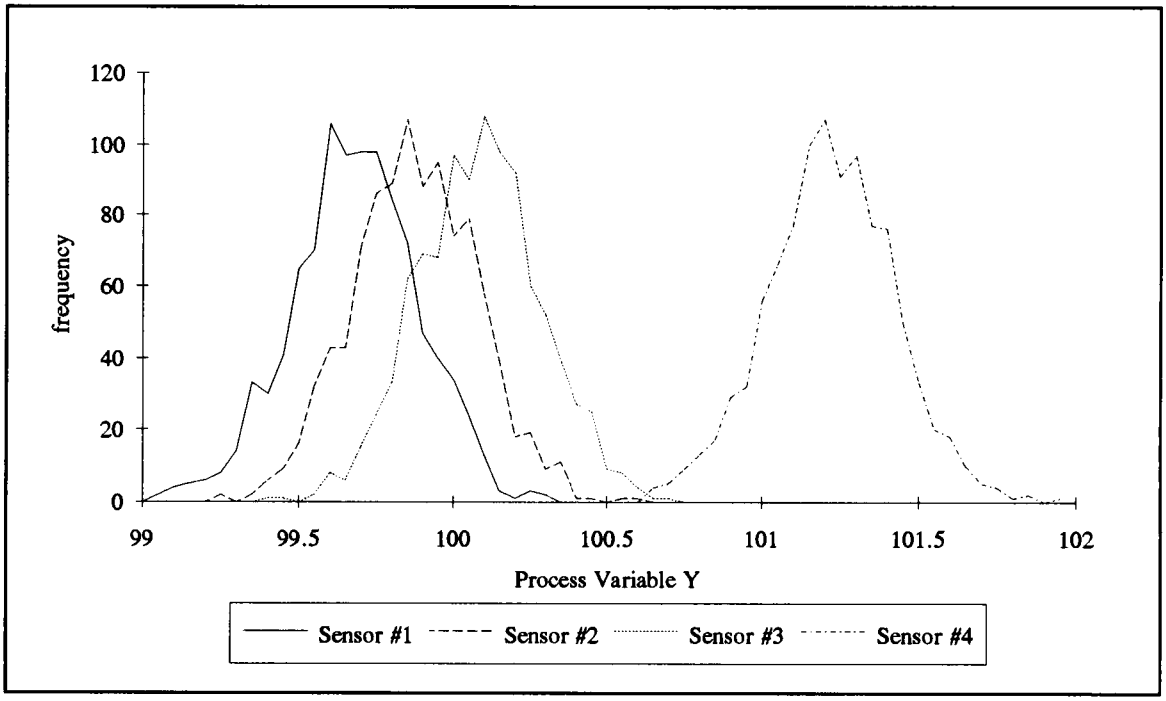


Figure 3.10 Example Distributions Of Three Normal And One Faulted Sensor.

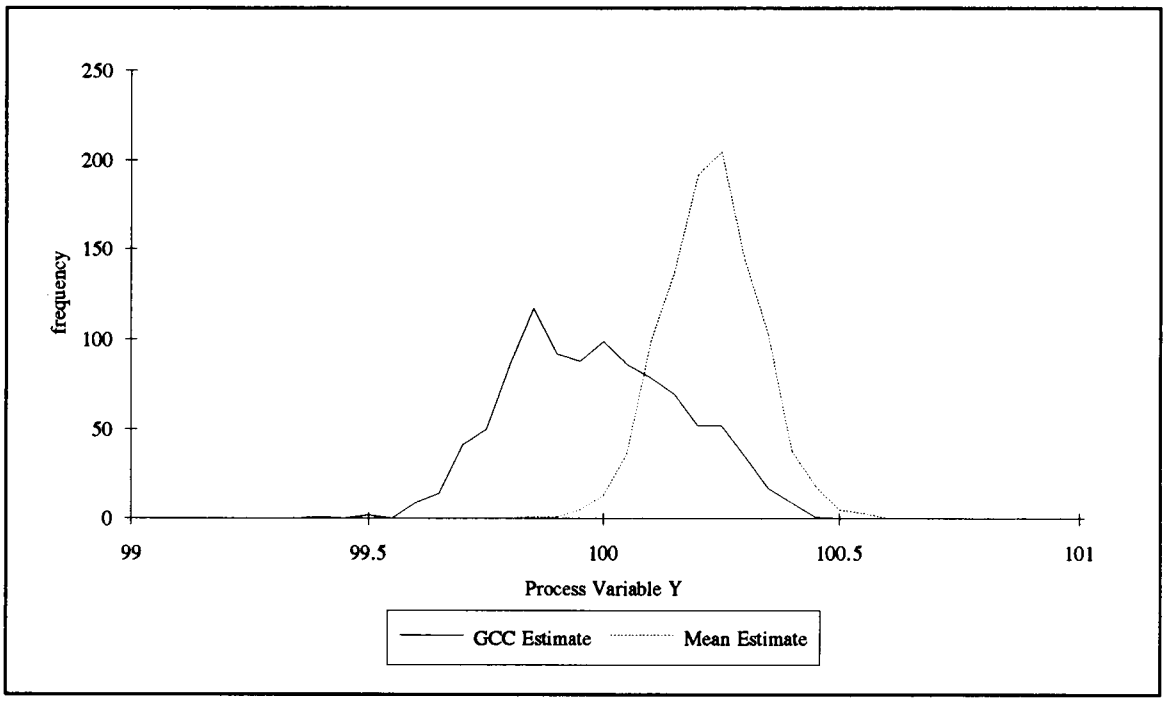


Figure 3.11 Comparison of a GCC Estimate vs. a Mean Estimate

and 0.80, respectively), the error bound will be determined for a confidence of 0.95 using the percentile of the Y_{GCC} data. This indicates an error bound of approximately (-0.3, +0.36), or in terms of the standard deviation, (-1.7σ, $+2\sigma$). Even though the mean estimator has an error bound of ± 0.2 units, it has a bias of 0.25 units, and is thus not as accurate as the GCC estimator.

Figure 3.12 demonstrates the effect of the sensor error on the process variable estimates for the GCC and mean algorithms. Since the mean estimator does not detect the faulted sensor and weights it less than the normal sensors, the estimate bias is a linearly increasing function of the faulted sensors error. However, the GCC estimator does detect the faulted sensor as a function of sensor error and maximum allowable bias, and reduces its effect on the estimate bias. Thus the GCC estimator can reduce the bias error as the faulted sensor error grows (or the maximum allowable bias is reduced).

3.4.2 Uncertainty of the Process Empirical Modeling Estimate

The Process Empirical Modeling (PEM) algorithm generates a multiple-input single-output (MISO), nonlinear polynomial that can predict the expected response of a process variable as a function of other physically related process variables. An example of the measured vs. predicted response of a reactor power model was shown in Figure 3.7. This model was generated to predict reactor power (in % of full power) using a power range monitor as output, and four input variables: 1) pressurizer level, 2) cold leg

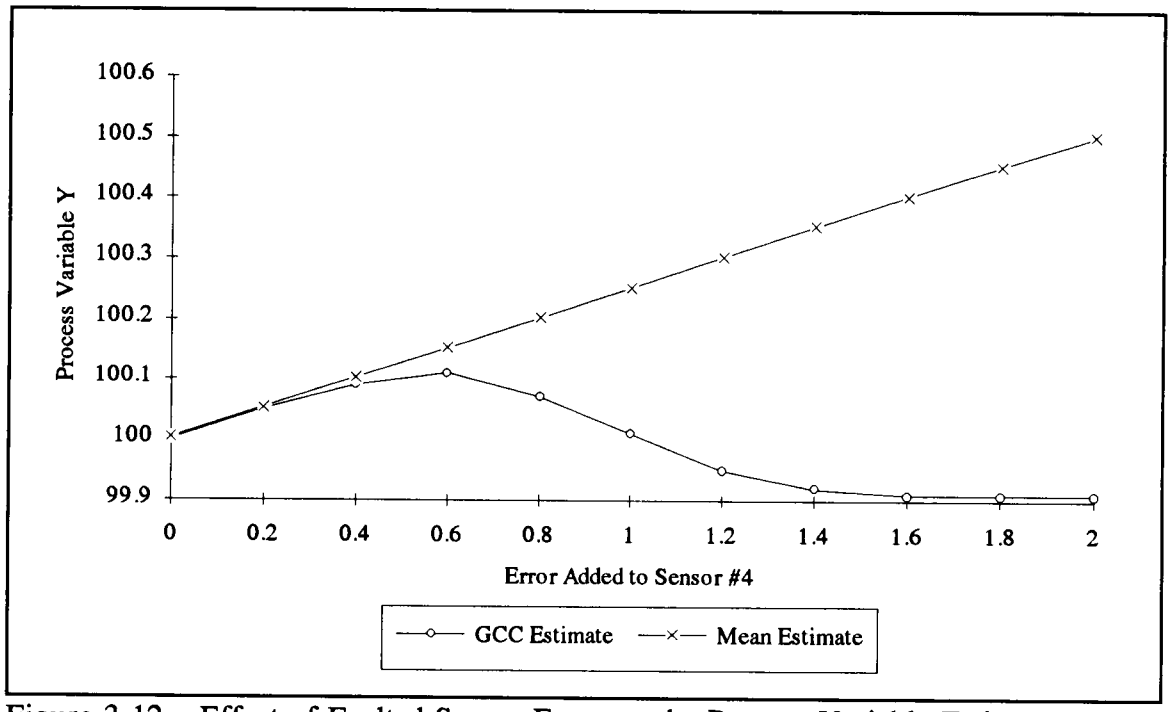


Figure 3.12 Effect of Faulted Sensor Error on the Process Variable Estimate.

temperature, 3) hot leg temperature, and 4) main steam pressure. To maximize the accuracy of the model, the range of data was limited from 98% to 101% of full power. In order to use this estimate for calibration verification, it is necessary to determine the error bounds of the model estimate.

The accuracy of a PEM model is based on the data that is used to create it (that is, the model prediction is compared to the actual output measurements that were used in the model development). A root mean square deviation is used to quantify the error that is inherent in the model:

$$e_{rms} = \sqrt{\frac{1}{S}\sum_{i=1}^{S} (x_i - p_i)^2} \tag{3.14}$$

where x_i and p_i are the measured and predicted values of the process variable, respectively for sample i, and S is the total number of samples. This uncertainty should be a characteristic of the model when used within its intended domain, and with all input signals behaving normally. In practice, however, the input signals to the model may have experienced some bias drift, thus potentially increasing the error in the prediction. The degree of error is a function of how sensitive the model is to a particular input variable. The general form of the PEM polynomial is given by;

$$Y_{PEM} = A_0 + \sum_{i=1}^{no.\,of\,terms} A_i \prod_{j=1}^{no.\,of\,inputs} x_j^{n_{ij}} \qquad (3.15)$$

where the A's are constant coefficients, the x's are process variable inputs, and the n's are exponents. In this case, the sensitivity of the output Y_{PEM} to an input variable can be measured by using the partial derivative of the polynomial to that input variable. Thus the bias of the PEM estimator may be affected by errors in the input signals.

Since Y_{PEM} is used as a redundant and diverse input to the GCC algorithm, the error bound and confidence of the PEM estimate should be at least as good as the sensors that it is modeling. For this application, the model estimates are treated like the actual sensor measurements. That is, the mean, standard deviation, skewness, and kurtosis are all calculated for the model estimate, and compared to the known behavior of a "calibrated" estimate. (The "calibrated" estimate represents the behavior of the model under the model's normal conditions). The model is input to the GCC algorithm as an additional channel, and will undergo the same analytical process as the real sensors (consistency checking, SPRT, etc.). Therefore the parameters that are calculated for the sensors (e.g. sensor bias) are also calculated for the model estimate, and will provide a measure of the accuracy of the estimate.

4. DETERMINATION OF SIGNAL DEVIATIONS FROM PROCESS VARIABLE ESTIMATE

4.1 Introduction

In the last chapter, an estimate was obtained for the true value of the process variable using redundant measurements. The estimate is assumed to represent the true value with an associated error bound and confidence. We can now analyze the signal measurements to quantify the deviation of the measured value from the estimate. Three basic methods are employed to determine this deviation. First, we calculate a set of sensor statistics over the sample space. The mean sensor deviation quantifies the sensor *bias* from the process variable estimate. An overall measure of sensor accuracy for a set of data can be described using the *mean-square error*. The mean, standard deviation, skewness, and kurtosis are also calculated to better characterize sensor data. Second, the generalized consistency checking algorithm is used to generate a mean cumulative inconsistency index (C_i), and the number of exclusions from the weighted estimate (EXCL) for each signal. The C_i parameter provides a measure of partial inconsistency, before a sensor is considered to be completely degraded. The EXCL parameter indicates what percentage of samples (or time) that a signal is declared completely inconsistent, and rejected as faulty. Finally, the sequential probability ratio test (SPRT) will be introduced. The SPRT allows the determination of two parameters; the mean number of samples to decision for a normal state (MSTDN), and the mean number of samples to decision for

a degraded state (MSTDD). These parameters provide a relative measure of the signal bias drift from a hypothetical normal distribution to a distribution with a bias drift, and can also be used as a precursor to incipient calibration failure.

4.2 Sensor Statistics

Certain statistics can be used to compare the current state of a sensor to a calibrated benchmark. For this project, we determine the mean sensor deviation and the mean-square error using Y_{GCC} as the true value of the process variable. In calculating these statistics, we will also determine the mean, variance, skewness, and kurtosis of a sensor.

The bias of a sensor is a measure of its mean deviation from the true value of the process variable. For this application, the *sensor bias* is defined to be

$$B_i \equiv \mu_i - \mu_{GCC} \tag{4.1}$$

where μ_i is the mean value of the measurements for sensor "i", and μ_{GCC} is the mean value of Y_{GCC} over the same sample space. The magnitude of the bias indicates the drift of the sensor mean, and the sign indicates the direction. Note that Y_{GCC}, and therefore μ_{GCC}, are not independent of the sensor measurements y_i, but are derived from them. Therefore the bias of normal sensors can be influenced to some degree by a degraded

sensor. However, when using several redundant sensors, the estimator Y_{GCC} will reduce or eliminate the influence of a degraded sensor. It is reiterated that if the results of these analyses become indeterminate, the calibration of one or more sensors cannot be verified using these techniques.

Another measure of the deviation of a sensor from the process variable estimate is the mean-square error. The mean-square error of the sensor i, using Y_{GCC} as the true value of the process variable, is given by

$$MSE\,[y_i] = E\,[\,(y_i - Y_{GCC})^2\,] \tag{4.2}$$

and is related to the sensor bias by

$$MSE\,[y_i] = V[y_i] + B_i^2 \tag{4.3}$$

The mean-square error describes a sensor's accuracy with respect to the process variable estimate by accounting for the *spread* of the measurements and the *shift* in the sensor mean.

As an example, refer to the distributions of artificial measurements for the three normal sensors and one degraded sensor (#4), shown previously in Figure 3.10. The

Table 4.1 Sensor Statistics for the Artificial Sensor Data Example

Sensor No.	Mean	Variance	Bias	MSE
1	99.7	0.04	-0.3	0.13
2	99.9	0.04	-0.1	0.05
3	100.1	0.04	+0.1	0.05
4	101.3	0.04	+1.3	1.73
Y_{GCC}	100.0	0.03	N/A	0.03

sensor statistics are presented in Table 4.1. These results show that the bias and MSE of the faulted sensor are not in agreement with the normal sensors. By properly selecting the GCC maximum allowable error, sensor #4 was excluded from the process variable estimate for most of the samples. Therefore its effect on Y_{GCC}, and thus the normal sensor bias and MSE, is minimized. Figure 4.1 illustrates the effect of the faulted sensor on the bias for all of the sensors. For this example, an allowable tolerance of 0.6 units was used in the GCC algorithm. As the error added to sensor #4 increases, the sensor bias for the normal sensors begins to change (the GCC estimate Y_{GCC} is shifting up in the direction of the faulted sensor). When the bias error of the faulted sensor reaches approximately 0.6 units, the sensor bias for the normal sensors begin to return to their original values (the GCC algorithm is excluding more of the faulted sensor measurements, causing Y_{GCC} to shift down towards its original value). It is clear from Figure 4.1 that sensor #4 is the faulted sensor.

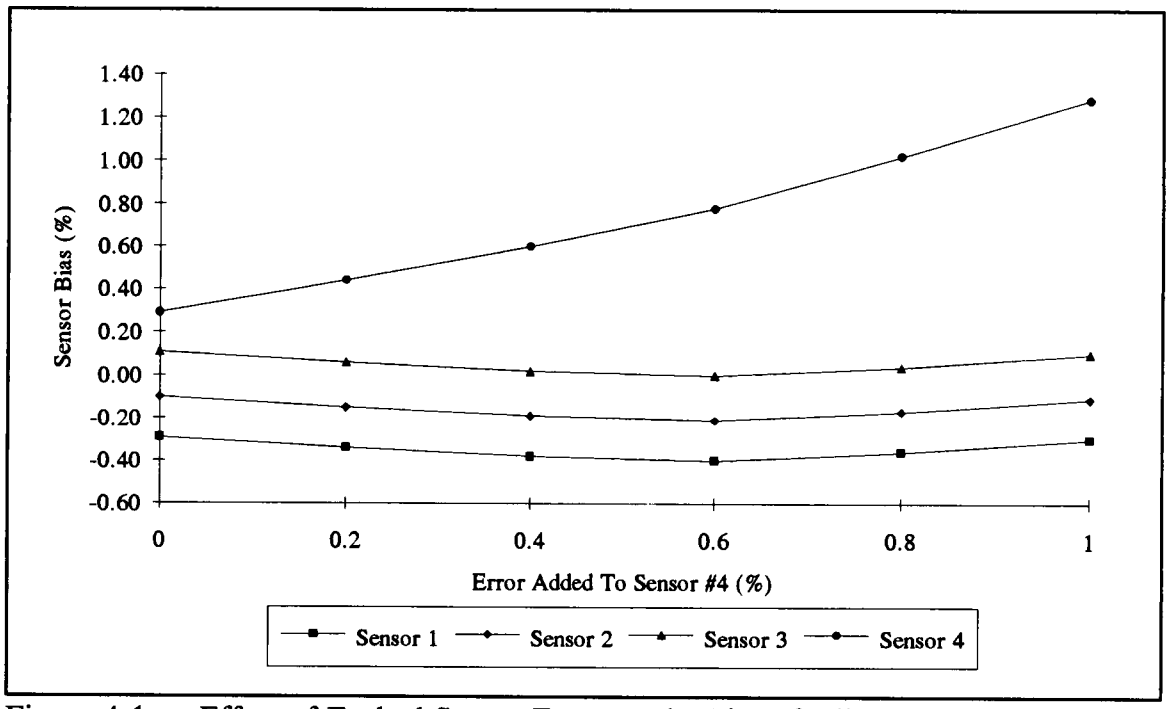


Figure 4.1 Effect of Faulted Sensor Error on the Bias of All Sensors

4.3 Cumulative Inconsistency Index

As discussed in Section 3.2, the GCC algorithm compares the difference between all pairs of redundant signals for a given sample against a specified maximum acceptable tolerance. If a pair of signals exhibits a difference greater than the sum of each sensor's tolerance, the cumulative inconsistency index of each of the pair is incremented by one

$$for \quad |m_i - m_j| > b_i + b_j \quad then \quad \begin{cases} C_i = C_i + 1 \\ C_j = C_j + 1 \end{cases} \tag{4.4}$$

where, for *N* signals, C_i can take on possible integer values from 0 to *N-1*. The cumulative inconsistency index of a signal is used by the GCC algorithm to determine a variable estimate to 1) provide a weighing factor for each sensor used in the averaging process, and 2) identify and exclude faulty signals from the estimate.

In the present work, C_i is used as an index to evaluate the calibration performance of a sensor. A mean C_i is calculated for each sample over a large set of steady-state measurements. This parameter is referred to as the *signal inconsistency index* (SII). Like C_i , the SII can also take on values from 0 to *N-1* but, because it is an average over many samples, its value may be a real number (i.e., non-integer). Lower values for a sensor's SII indicate good consistency while higher numbers indicate increasing inconsistencies. The SII gives an indication of the average behavior of a sensor with respect to consistency

with other redundant sensors.

Another parameter of interest calculated by the GCC algorithm is the percentage of samples for each sensor that are excluded from the weighted estimate (EXCL). EXCL gives the total percentage of time that a sensor is expected to be out of tolerance with all of its neighbors. This factor is not useful for the purposes of verifying the calibration state of a sensor (its value should be zero for calibrated sensors), but can give an indication of how severely a sensor is out of tolerance.

Once again, refer to the distributions of the artificial measurement of the three normal sensors and one degraded sensor shown previously in Figure 3.10. Table 4.2 shows the results of the GCC algorithm applied to the artificial data. The SII calculated for the normal signals results in a value of less than one, since the only source of inconsistencies comes from the faulted sensor #4. However, the faulted sensor has an SII greater than two, due to the fact that it is often inconsistent with more than one of its

Table 4.2 GCC Results for the Artificial Sensor Data Example

Sensor No.	SII	EXCL (%)
1	0.47	0.10
2	0.33	0.00
3	0.06	0.00
4	2.17	43.60

neighbors for a given sample. The table also shows that sensor #4 was excluded from the GCC estimate for 43.6% of the samples. Finally, the effect of the error added to sensor #4 on the SII of the normal sensors is shown in Figure 4.2. The figure shows the SIIs of the normal sensors increase until sensor #4 becomes excluded from the process variable estimate. A discussion on the adequacy of these values for the SII is presented in Chapter 5.

4.4 Sequential Probability Ratio Test

The Sequential Probability Ratio Test (SPRT) is a cumulative log likelihood ratio algorithm that can test a random variable against a hypothesis and one or more alternatives. It provides an efficient method of determining whether a random variable belongs to a characteristic set H_0 , or to an alternative set H_1 . For this application, the hypothesis H_0 represents the normal, calibrated state of the sensor, while H_1 represents the degraded, uncalibrated state of the sensor. A major advantage of the SPRT over other test procedures is that it does not require a pre-determined sample size, N, to make a decision. The number of samples required by the SPRT to make a decision, n, is a random variable, and is a measure of the test performance for a set of samples. The value of n is typically less than N for the same level of confidence in the test result (i.e., the missed and false alarm probabilities are equal) . Using the parameter n, the method is very useful for trending the calibration state of a sensor, and detecting an incipient calibration failure. In this sense, the SPRT is more efficient than other test procedures.

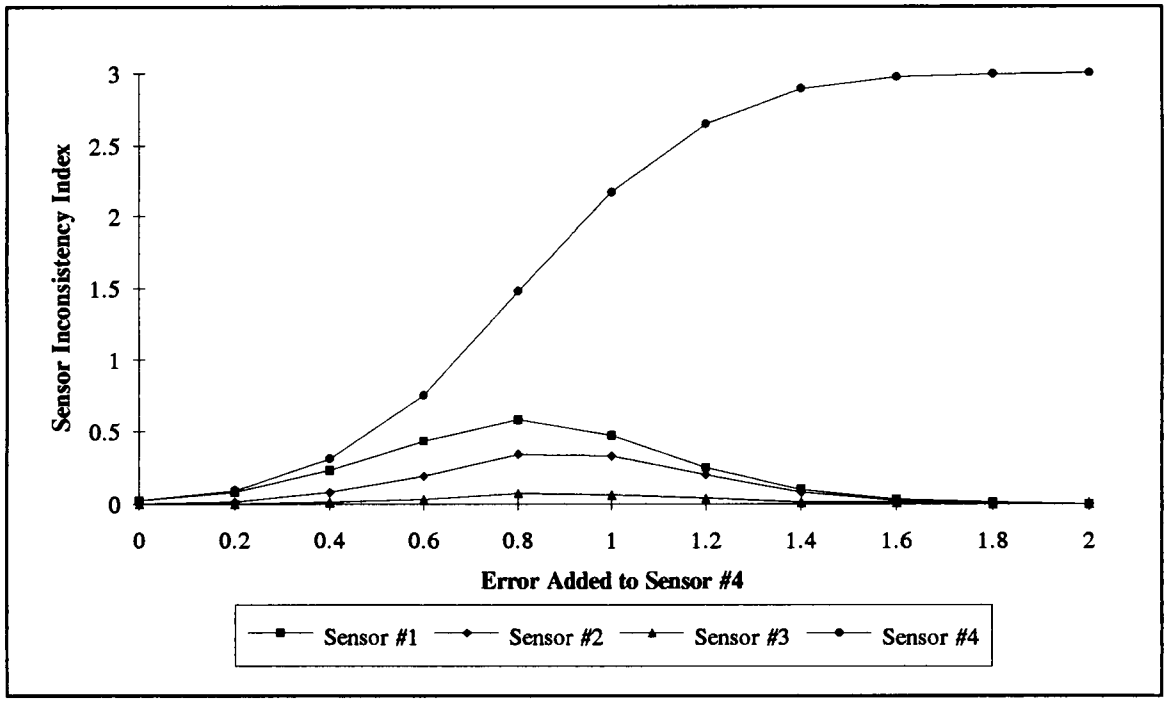


Figure 4.2 Effect of Faulted Sensor Error on the SII of all Sensors.

However, if the number of samples is pre-determined, then there is no advantage in using the SPRT.

The bases for the SPRT requires that a set of samples (x_1 , x_2 , ... , x_n) are classified into one of three mutually exclusive categories; 1) H_0 is accepted as true, 2) H_1 is accepted as true, or 3) neither H_0 nor H_1 is accepted as true. If category 1 or 2 occurs, then a decision is made and the test is terminated. If category 3 occurs, then the test is inconclusive, and an additional sample is drawn. The following inequalities define the acceptance criteria for H_0 and H_1

$$for \quad \frac{p_{1n}(x_1, x_2, \ldots, x_n)}{p_{0n}(x_1, x_2, \ldots, x_n)} \leq A, \quad H_0 \ holds \tag{4-5a}$$

$$for \quad \frac{p_{1n}(x_1, x_2, \ldots, x_n)}{p_{0n}(x_1, x_2, \ldots, x_n)} \geq B, \quad H_1 \ holds \tag{4-5b}$$

where p_{1n} and p_{0n} are the probability density functions for H_1 and H_0 for the n samples, (x_1 , x_2 , ... , x_n). The parameters A and B are defined to be the normal threshold (for H_0 acceptance) and the degraded threshold (for H_1 acceptance), respectively, and are given by

$$A = \frac{\beta}{1-\alpha} \tag{4-6a}$$

$$B = \frac{1-\beta}{\alpha} \tag{4-6b}$$

where α and β are the false alarm and missed alarm probabilities. Equations (4-6) are derived in reference [8]. Assuming that each sample x_i is independent, we can expand the probability density functions p_{0n} and p_{1n} , and form the ratio p_{1n} /p_{0n} as follows.

$$\frac{p_{1n}(x_1, x_2, \ldots, x_n)}{p_{0n}(x_1, x_2, \ldots, x_n)} = \frac{p_1(x_1)\, p_1(x_2) \ldots p_1(x_n)}{p_0(x_1)\, p_0(x_2) \ldots p_0(x_n)} \tag{4-7}$$

Define

$$\lambda_i = \ln \frac{p_1(x_i)}{p_0(x_i)} \tag{4-8}$$

Then the logarithm of Equation (4-7) may be expressed as

$$\Lambda_n = \lambda_1 + \lambda_2 + \ldots + \lambda_n \tag{4-9}$$

where Λ_n is the logarithm of the left hand side of Equation (4-7). We want Equation (4-9) to be expressed in a recursive form

$$\Lambda_n = \Lambda_{n-1} + \lambda_n \tag{4-10}$$

Finally, the acceptance criteria for H_0 and H_1 are expressed as

$$for \quad \Lambda_n \leq \ln A, \quad H_0 \ holds \tag{4-11a}$$

$$for \quad \Lambda_n \geq \ln B, \quad H_1 \ holds \tag{4-11b}$$

Equations (4-10) and (4-11) are the basis for this application of the SPRT.

The specific form of λ_i depends upon the assumed probability density functions p_{0n} and p_{1n}. For this application, we assume that the data exhibits a Gaussian distribution. This assumption is validated by calculation of statistics as discussed in Chapter 3. In order to satisfy the assumption inherent in Equation (4-7), the samples x_i must be independent. To achieve this, we will use the *residual* of the sensor data about its mean

$$s_i = y_i - Y_{GCC,\,i} \tag{4-12}$$

where y_i is the measurement and $Y_{GCC,\,i}$ is the estimate of the i-th sample. Using the residual as the random variable of interest, the probability density functions p_{ji} ($i=1,2,\ldots,n$ and $j=0,1$) are given by

$$p_{ji} = \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left\{\frac{-(s_i-\mu_j)^2}{2\sigma_j^2}\right\} \qquad (4\text{-}13)$$

For the bias degradation, we take $\sigma_0 = \sigma_1 = \sigma$ and $\mu_0 = 0$ so that Equation (4-10) becomes

$$\Lambda_n = \Lambda_{n-1} + \frac{\mu_1}{\sigma^2}\left\{s_n - \frac{\mu_1}{2}\right\} \qquad (4\text{-}14)$$

In this expression, μ_1 is the difference of the means for H_0 and H_1 , and represents the mean of the maximum allowable bias for a sensor to be considered normal.

The determination of the threshold limits A and B is subjective, and is a function of the uncertainty defined by α and β that is considered to be acceptable. The value of the probabilities α and β are defined by the choice of a critical cutoff, y_c. For a given sample, if the value of s_i is less than or equal to y_c, then λ_i is negative, and Λ_i moves in the direction of H_0 . If s_i is greater than y_c, then λ_i is positive, and Λ_i moves in the direction of H_1 . Figure 4.3 illustrates the relationship between α and β. Since the combination of α and β represents the total probability of making an incorrect decision (i.e., accepting H_0 when H_1 is true, or accepting H_1 when H_0 is true), it is desirable to

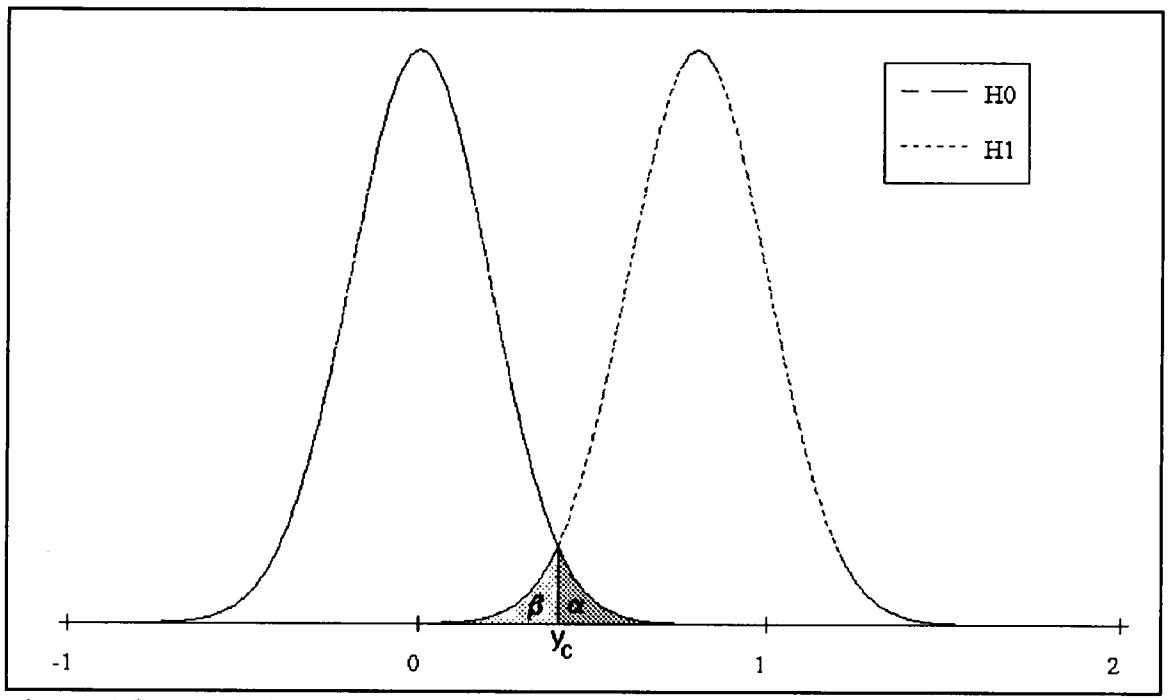


Figure 4.3 Relationship Between the False and Missed Alarm Probabilities.

minimize their sum. By examining Figure 4.3, it is apparent that the sum of the areas labeled α and β are at a minimum when $y_c = \frac{1}{2}\,\mu_1$. Equation (4-14) is consistent with this choice for y_c.

An important parameter for this application is the mean number of samples that are required for the acceptance of H_0 or H_1 to occur. Denote the sample space S as a 1 x s partitioned set

$$S = \{S_{1,0}, S_{2,0}, \ldots, S_{m,0} \mid S_{1,1}, S_{2,1}, \ldots, S_{p,1}\} \qquad (4\text{-}15)$$

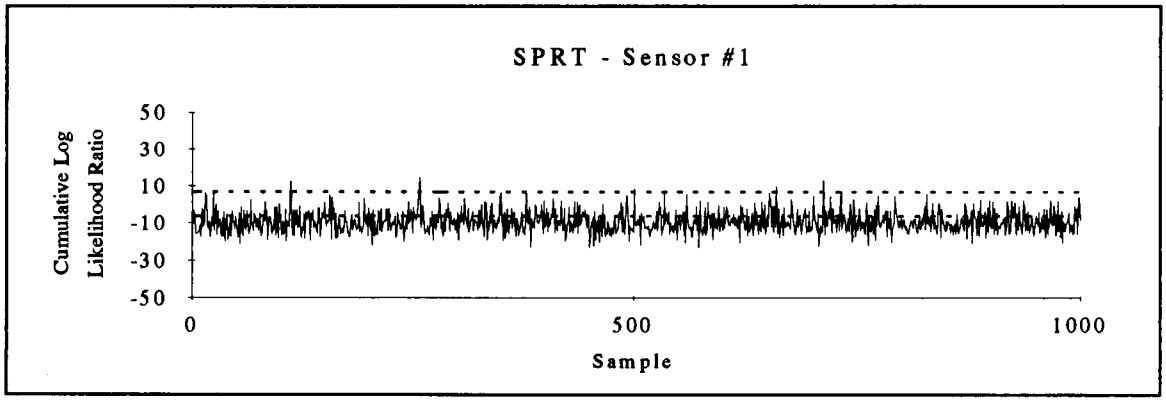
where $S_{i,0}$ and $S_{j,1}$ are sample subsets that make up one SPRT decision cycle for acceptance of H_0 and H_1 respectively, and $s = m + p$. The total number of times in S that H_0 is accepted is equal to m, and the total number of times that H_1 is accepted is equal to p. For completely normal signals, all of the $S_{j,1}$ subsets are null sets (i.e., $p = 0$), and for completely degraded signals, all of the $S_{i,0}$ subsets are null sets (i.e., $m = 0$). From this we define two parameters; 1) the mean number of samples to a normal decision, MSTDN, and 2) the mean number of samples to a degraded decision, MSTDD. They are expressed as

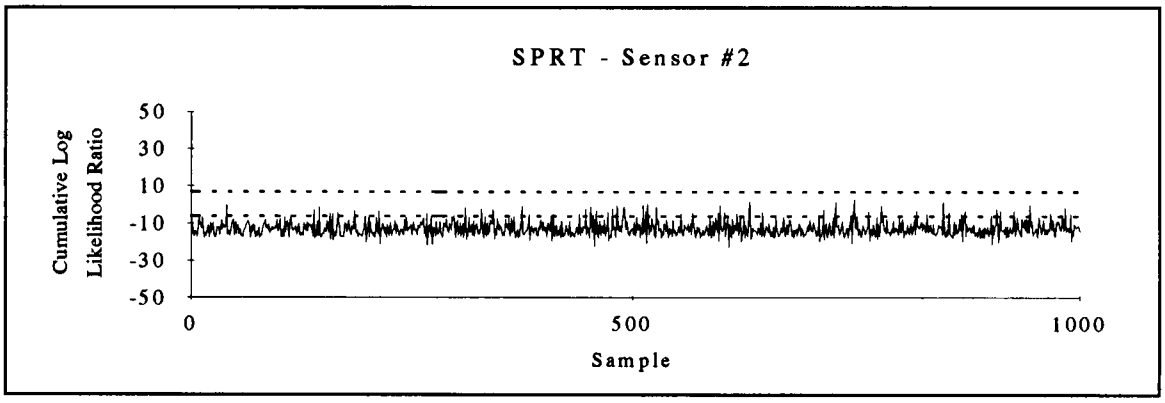
$$MSTDN = \frac{n}{m} \qquad (4\text{-}16a)$$

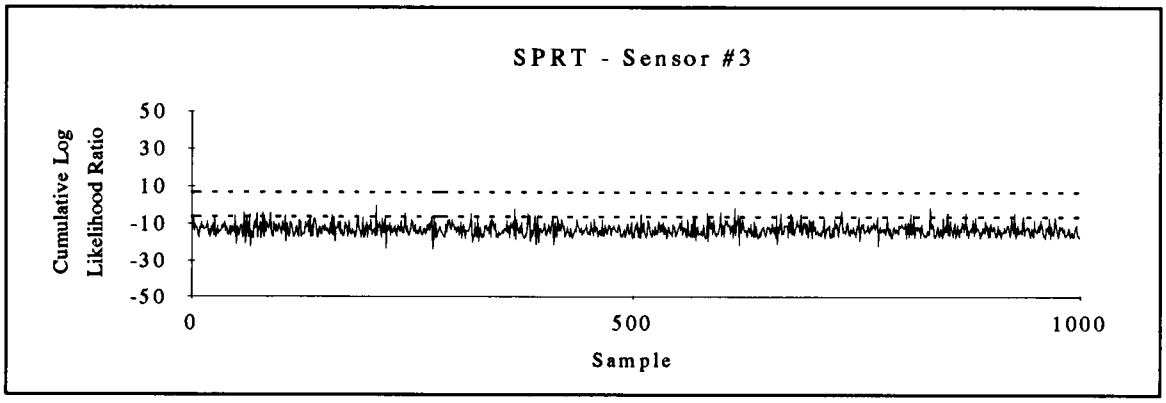
$$MSTDD = \frac{n}{p} \qquad (4\text{-}16b)$$

where n is the total number of samples in the sample space S. If the residuals of the measurements are small compared to y_c then inequality (4-11a) will be satisfied over a small number of samples, and MSTDN will be small (large m). If they are large compared to y_c then inequality (4-11b) will be satisfied over a small number of samples, and MSTDD will be small (large p). Values of the residuals in the neighborhood of y_c will result in large values of both MSTDN and MSTDD . For calibrated sensors, the limit of the MSTDD is expected to approach infinity, since no sample sets should yield an acceptance of H_1 (i.e., $p = 0$). The value of MSTDN can be trended from a calibrated baseline to detect incipient bias degradation.

The artificial sensor data in Figure 3.10 is used again to demonstrate the application of the SPRT. Figure 4.4 shows the behavior of Λ_i as a function of time of three normal sensors, and one degraded sensor. The two dotted lines are the upper (ln(B), acceptance of H_1), and the lower (ln(A), acceptance of H_0) acceptance criteria of the SPRT. As each of the test cycles reaches a limit, Λ_i is reset to zero, and the test begins with a new sample. Note that the normal sensors appear consistently below the lower acceptance criteria. This is because, for most samples, the value of Λ_i is low enough to be declared normal using a single sample. As can be seen in the figure, the faulted sensor #4 is consistently declared to be degraded. The values for the MSTDN and MSTDD parameters are presented in Table 4.3. The table shows that sensor #4 was







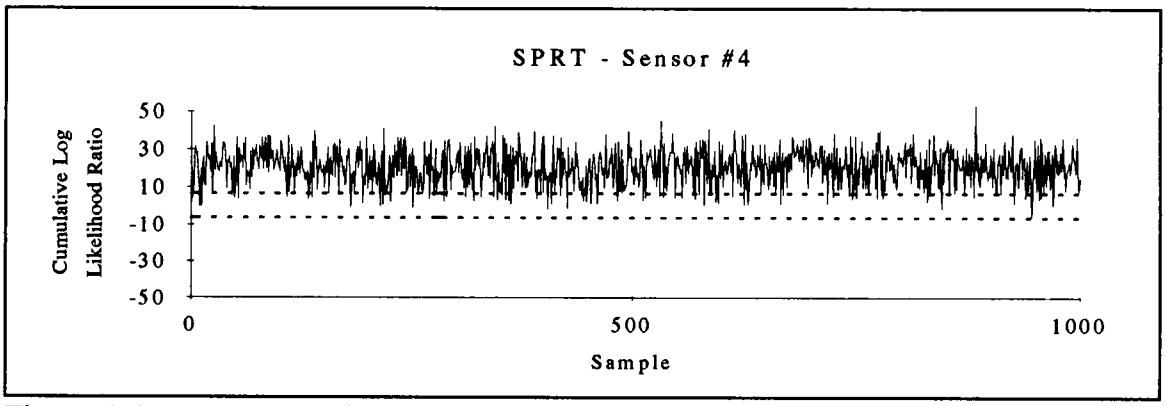


Figure 4.4 Example of SPRT Application to the Artificial Sensor Data Example.

Table 4.3 Mean Samples to Decision for the Artificial Sensor Data Example

Sensor No.	MSTDN	MSTDD
1	1.41	111.11
2	1.08	∞
3	1.05	∞
4	∞	1.09

never declared to be normal for any of the sample subsets, and was strongly degraded. Note that sensor #1 has a low value for the MSTDN, but also shows some weak indication of degradation (MSTDD = 111.11). This is primarily due to the tight tolerance used for the maximum allowable bias in the SPRT algorithm and the tendency of the GCC estimate to be centralized to the spread of sensor readings. Thus, the outlying sensors may show some smaller values for the MSTDD. However, the value of the MSTDN is small enough to infer that sensor #1 is normal (in fact, the ratio MSTDN/MSTDD is equal to 79, indicating that sensor #1 was declared normal 79 times more than it was declared abnormal).

There may be instances where the values for MSTDN and MSTDD can lead to greater ambiguity. Figures 4.5 and 4.6 show the effect of the faulted sensor error on all of the sensors. As the error applied to sensor #4 increases, the values of the MSTDN increase, and the values of the MSTDD decrease, for all of the sensors (because of the scale of the vertical axis, the values of the MSTDD of sensors 2 and 3 do not appear in

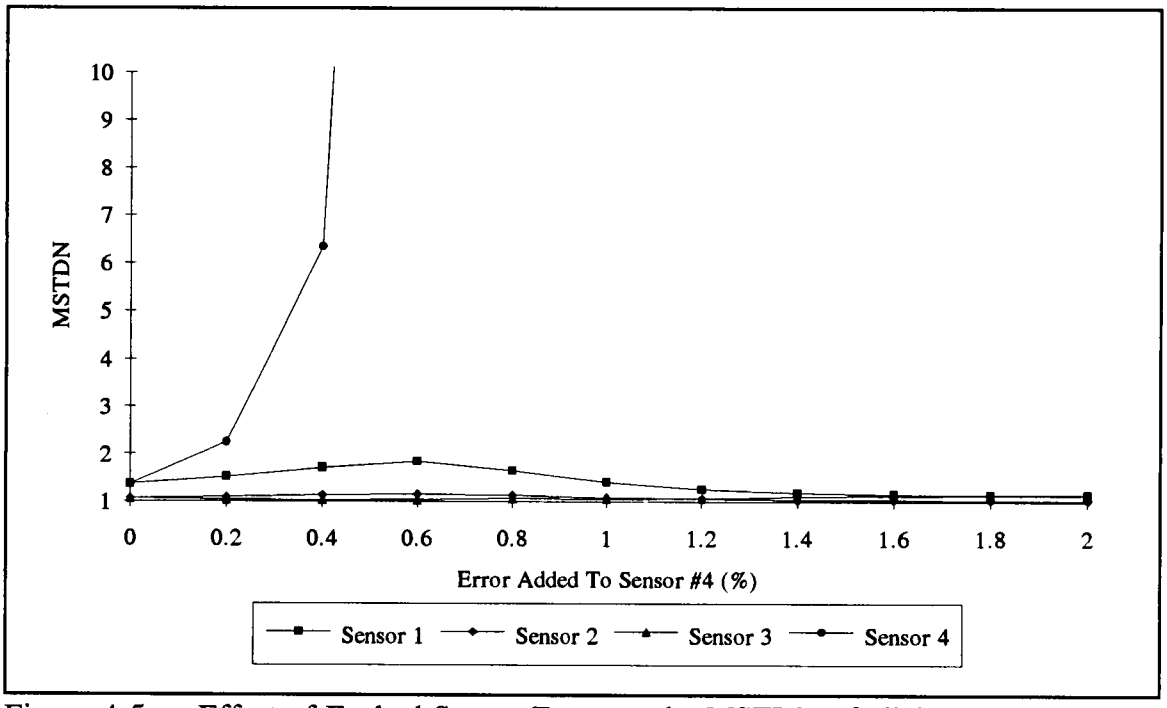


Figure 4.5 Effect of Faulted Sensor Error on the MSTDN of all Sensors.

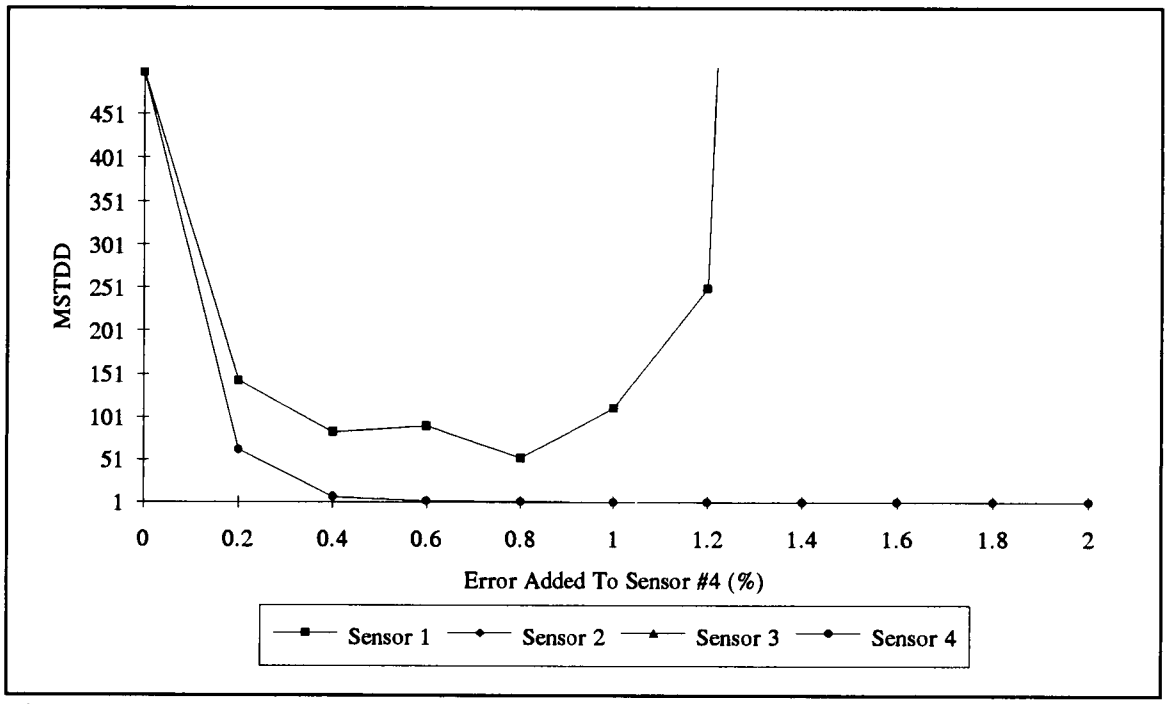


Figure 4.6 Effect of Faulted Sensor Error on the MSTDD for all Sensors.

Figure 4.6). The MSTDN and MSTDD of the normal sensors return to nominal values after sensor #4 has degraded enough to be excluded from the process variable estimation. Although there appears to be some ambiguity between sensors 1 and 4 in Figure 4.6, it is clear in Figure 4.5 that sensor #4 has deviated from its nominal value. The sensitivity of the MSTDN makes it a particularly valuable parameter for detecting a bias drift.

The next example better illustrates the trending capability of the SPRT. Instead of applying a constant bias of one unit to sensor #4, the bias is linearly increased from zero to one unit over the entire sample space. Thus at sample 1 there is zero bias error added, at sample 500 there is a 0.5% bias error added, and at sample 1000 there is a 1% bias error added. The resulting behavior of the Λ_i is shown in Figure 4.7. This serves to demonstrate how the value of Λ_i varies with increasing sensor bias error.

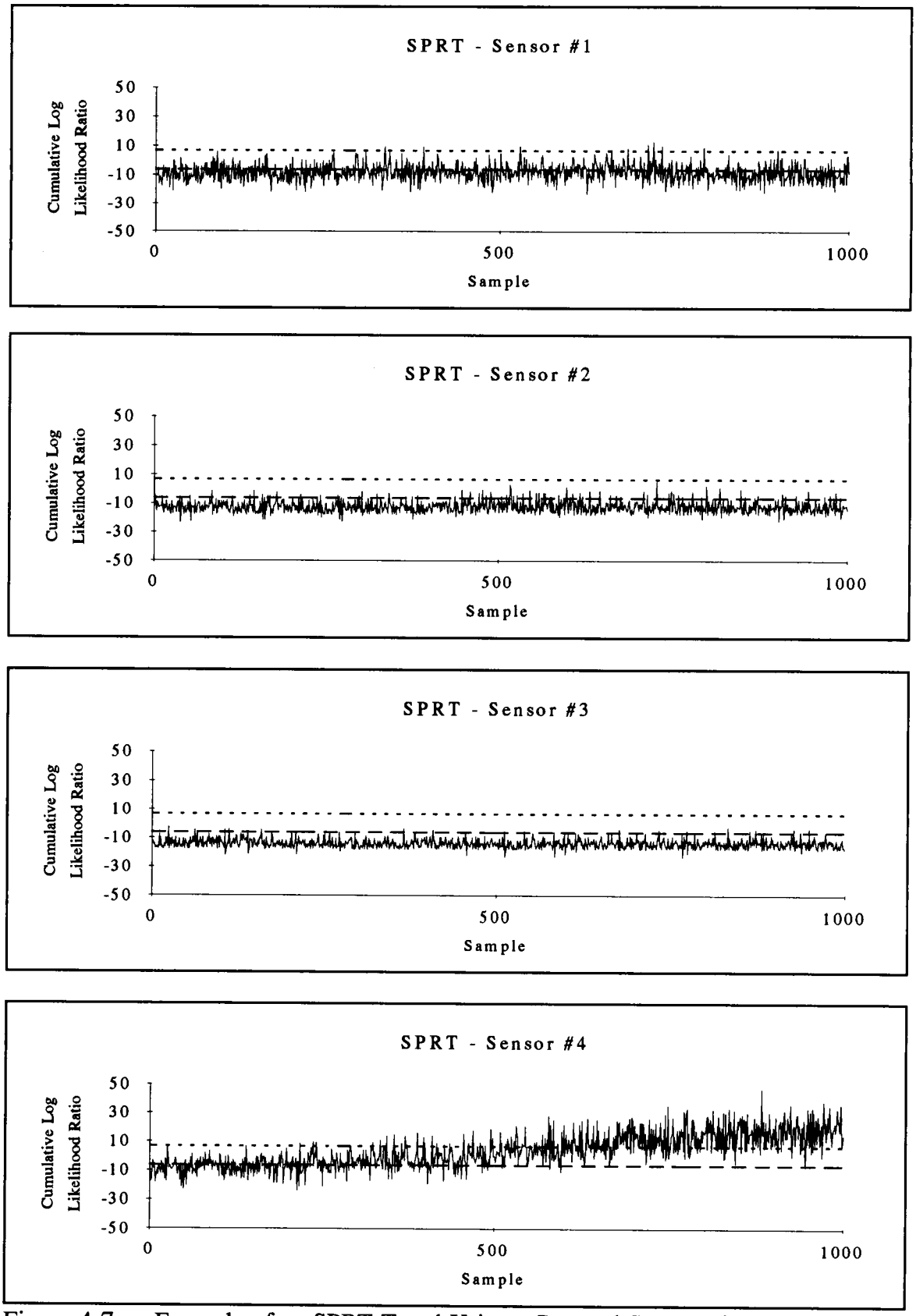


Figure 4.7 Example of an SPRT Trend Using a Ramped Sensor Bias

5. EVALUATION OF CALIBRATION ADEQUACY

5.1 Introduction

The objective of this chapter is to propose a method to help evaluate the adequacy of a sensor's calibration state based upon the tests discussed in Chapter 4. The method will compare changes in the sensor characteristics from a known calibrated baseline, and generate an *index of performance* relative to the baseline. This provides a means to trend sensor behavior and allows personnel to anticipate potential problems and maintenance needs. The determination of the point where the index becomes unacceptable requires expert judgement. Ultimately, it should be based on established technical specifications for the affected sensors.

The method will borrow a concept from the theory of fuzzy sets called a *fuzzy membership function*. In this application, the membership function serves as the index of performance for the calibration state of the sensor. The parameters that are needed to define the membership functions are derived from the sensor baseline data, and/or the specified tolerance of the sensor. Trends of the membership functions provide a means of detecting incipient calibration failures.

5.2 Fuzzy Membership Functions

In classical set theory, sensor signals can be categorized into two sets

$$A = \{ x | x \text{ is acceptable} \} \tag{5.1a}$$

$$\overline{A} = \{ x | x \text{ is unacceptable} \} \tag{5.1b}$$

where x is a signal value. The definition of an acceptable sensor is based on some predetermined bounds as discussed in Chapter 2. For example, an acceptable RTD may have specified bounds of $\pm$ 2° F. This would give the following set definitions

$$A = \{ x | \ abs(T_{est} - x) \leq 2°F \} \tag{5.2a}$$

$$\overline{A} = \{ x | \ abs(T_{est} - x) > 2°F \} \tag{5.2b}$$

While this does provide criteria for deciding whether a signal is good or not, it does not allow for assessment of the relative accuracy of sensors that fall into the acceptable range, or tracking of trends that may occur over time. Such characteristics (relative accuracy or deviations) can be quantified using statistical parameters such as standard deviation and mean. However, the use of fuzzy membership functions provides a more structured method for tracking sensor deviations over time.

A fuzzy set is a grouping of elements into classes that do not have sharply defined boundaries. A fuzzy set A in X is defined as a set of ordered pairs

$$A = \{ x, \chi_A(x) \}, \qquad x \in X \tag{5.3}$$

where $\chi_A(x)$ is the *fuzzy membership function* of x in set A. The membership function is a measure of the degree of conformity of x to the characteristics of set A. The value of $\chi_A(x)$ ranges from 1 (complete conformity) to 0 (complete non-conformity). The exact form of $\chi_A(x)$ is somewhat subjective, and should be determined in the context of what class of elements is desired, and how restrictively we wish to (or are able to) define that class.

Following our sensor signal example above, the definition of the fuzzy set of "acceptable" sensors may be given as

$$A = \{ (x , \chi_A(x)) , x \approx T_{est} \} \tag{5.4}$$

which is interpreted as the set of all x that are approximately equal to T_{est}, with a degree of membership in A equal to $\chi_A(x)$. In this case, we must choose a membership function such that

$$\chi_A(x) = 1, \quad for\ x = T_{est} \tag{5.5a}$$

$$\chi_A(x) = 0, \quad for\ x > T_{est} \pm \Gamma \tag{5.5b}$$

where Γ is some absolute threshold beyond which the signal is clearly unacceptable.

As was mentioned above, the choice of a membership function is partially subjective, but should reflect a qualitative judgement on what weighting should be assigned to different values of the variable of interest. For example, a linear membership function could be applied to our sensor problem such that the above boundary conditions of 0 and 1 are met. However, this would assign signals that are just beyond our tolerance Γ a value of 0, or completely unacceptable. Kandel [9] gives an example of a bell shaped membership function called a π-number which can be fit to our sensor example in such a way as to place a greater weighing on all signals within our nominal tolerance, yet still quantify the relative accuracy of signals just outside this bound. The π-number is defined as follows

$$\chi_{pi}(x) = \begin{cases} \frac{2}{\beta^2}(x-p+\beta)^2 & for\ p-\beta \le x \le p-\frac{\beta}{2} \\ 1-\frac{2}{\beta^2}(x-p)^2 & for\ p-\frac{\beta}{2} \le x \le p+\frac{\beta}{2} \\ \frac{2}{\beta^2}(x-p-\beta)^2 & for\ p+\frac{\beta}{2} \le x \le p+\beta \end{cases} \tag{5.6}$$

where β is the *bandwidth* and p is the *peak-point* of the membership function. The bandwidth is the half-width of the bell curve at which $\chi_{pi}(x)$ is equal to 0.5. In our sensor example, this may be equivalent to twice the allowable signal tolerance. The peak-point corresponds to a value of 1 for $\chi_{pi}(x)$, and represents the target value T_{est} for the process variable of interest. A suitable application of the π-number is the sensor bias as defined by Equation (4.1). Figure 5.1 shows a plot of the π-number with $p = 0$ (corresponding to a desirable value of bias $B_i = 0$), and $\beta = 1.2$ (corresponding to a maximum allowable bias of twice the allowable signal tolerance for one sensor). The bandwidth was chosen so that $\chi_{pi}(x)$ is equal to 0.5 at a value for B_i equal to the allowable signal tolerance. This allows the analyst to track the severity of the bias drift outside of the allowable tolerance. Another useful membership function is the z-curve that was previously introduced in Section 3.2 as a GCC algorithm weighting function. The general form of the z-curve is given by equation (5.7), and is illustrated in Figure 5.2 as a GCC weighting function with $p = 0$ and $\beta = 4$ (reproduced from Figure 3.4). This type of membership function will also be used for the normalized signal inconsistency index (NSII) and the SPRT parameters, MSDTN and MSTDD.

$$\chi_z(x) = \begin{cases} 1 & \text{for } x \le p \\ 1 - \frac{2}{\beta^2}(x-p)^2 & \text{for } p \le x \le p + \frac{\beta}{2} \\ \frac{2}{\beta^2}(x-p-\beta)^2 & \text{for } p + \frac{\beta}{2} \le x \le p + \beta \\ 0 & \text{for } p + \beta \le x \end{cases} \tag{5.7}$$

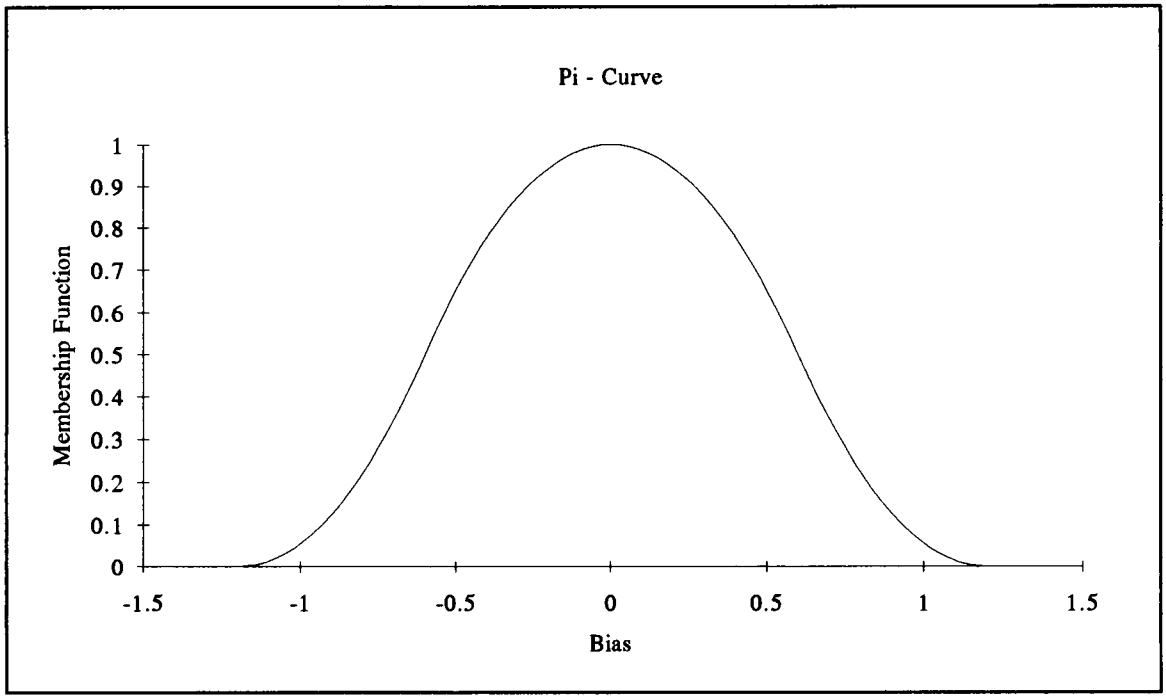


Figure 5.1 Example of a π-Number as a Membership Function for Sensor Bias.

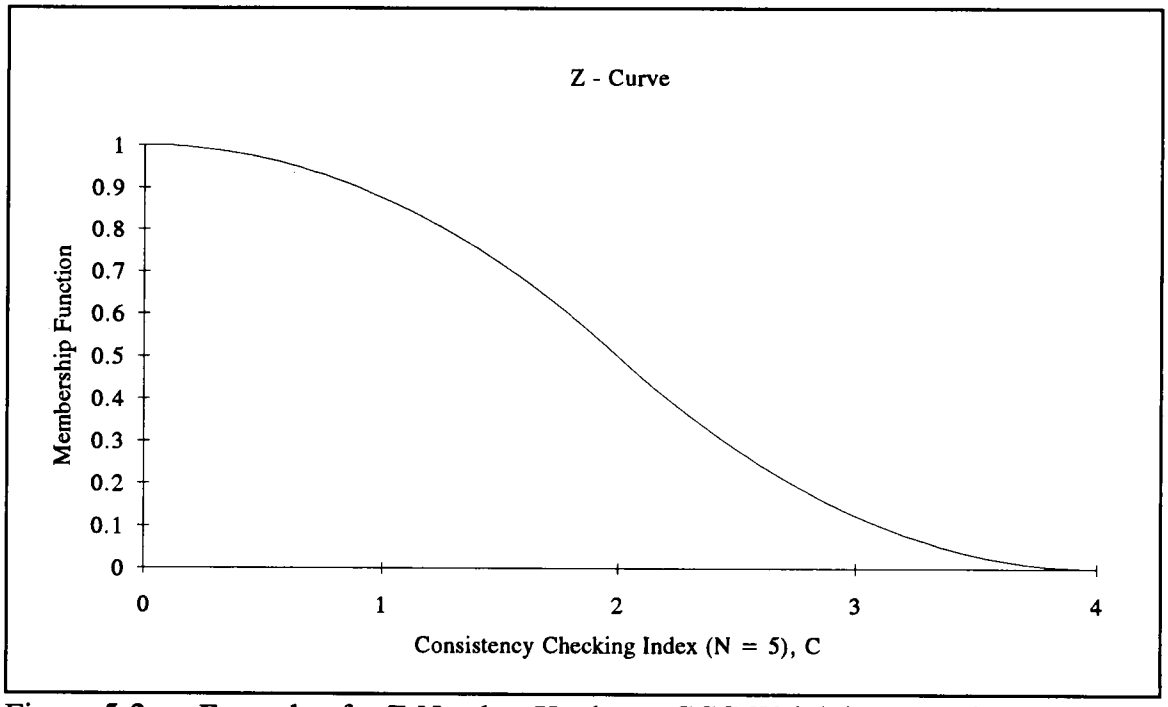


Figure 5.2 Example of a Z-Number Used as a GCC Weighting Function.

5.3 Signal Tolerance for Calibration

In Chapter 2, we discussed the basis for the calibration of instruments. The limits, or *tolerance*, that can be defined for determining the adequacy of instrument calibration are presented in this section. An instrument tolerance can be *prescribed* or *learned*. A prescribed tolerance typically originates from instrument vendor recommendations. The plant accident analysis (implemented through the Technical Specifications) may also place requirements on the minimum acceptable tolerance of an instrument. A prescribed tolerance is always the absolute limit to judge the acceptability of the calibration state of an instrument, since it is typically used as an assumption for analysis and operations. Learned tolerance can be derived from a sensor's historical behavior using the techniques discussed in Chapters 3 and 4. A sensor or a group of sensors that is known to be calibrated can provide a baseline consisting of any set of performance characteristics (e.g., variance, bias, SII, MSTDN, and MSTDD). Learned tolerance can provide a more accurate measure of an instrument's calibration state, and allow trending of characteristics before the prescribed tolerance is challenged.

The performance characteristics of interest for this application are divided into two categories, 1) as input to the process variable estimation algorithms and, 2) as results from the signal deviation tests. Table 5.2 outlines the characteristics of interest. To generate a process variable estimate using the GCC algorithm, the error bound for each sensor must be provided. For a Gaussian distribution, this is best determined using the

Table 5.1 Performance Characteristics for Calibration Verification

Parameter	Notation	Comment
Process Variable Estimate		
Standard Deviation	σ	May be used to learn error bound. Check on sensor noise characteristics.
Skewness	$\mu 3$	Verification of Gaussian distribution. Check on sensor noise characteristics.
Kurtosis	$\mu 4$	Verification of Gaussian distribution. Check on sensor noise characteristics.
Signal Deviation from Baseline		
Sensor Bias	B	Normal sensor deviation from the process variable estimate.
Signal inconsistency index	SII	Consistency checking among redundant sensors (normal value ~ 0).
Mean samples to normal decision	MSTDN	Comparison of sensor against its own history - normal behavior (ideal value ~ 1).
Mean samples to degraded decision	MSTDD	Comparison of sensor against its own history - degraded behavior (ideal value ~ ∞).

standard deviation of the sensor when it is known to be calibrated. Using a Gaussian distribution, we may set the error bound of a sensor equal to a multiple of the standard deviation, such that a desired confidence is obtained. (e.g., using an error bound of 3σ corresponds to a confidence of $> 99.7\%$). The standard deviation can also provide the basis for the mean value of the degraded hypothesis H_1 used in the SPRT algorithm. It is reasonable to use some multiple of the standard deviation to represent the maximum allowable bias, μ_1 , of the degraded hypothesis H_1. To help validate the assumption of a Gaussian distribution, the skewness and kurtosis of the sensor signals are also calculated. Since the parameters, σ, μ_3, and μ_4, adequately describe the distribution of sensor data for a steady-state condition, changes from the baseline may indicate a change in the sensor noise characteristics. Such changes question the validity of proceeding with these tests, and are therefore useful parameters to trend.

The baseline results from the sensor deviation tests provide the performance characteristics for a calibrated sensor. The sensor bias (B) and the signal inconsistency index (SII) take advantage of the sensor redundancy to characterize the sensors relative to the process variable estimate and to each other. In addition, the inclusion of a process empirical model (PEM) estimate as another "sensor" allows comparison to diverse process variables. The nominal values for the sensor bias vary, but will typically be much less than the allowable error bound, and (because the estimate is a weighted average) will distribute themselves equally around the process variable

estimate. Ideally, the value for the SII will be approximately zero, since normal redundant sensors will rarely be inconsistent with each other.

The last two parameters in Table 5.1 are generated from the SPRT algorithm, and represent comparison of a sensor against itself over time. For a calibrated sensor the MSTDN will be ideally equal to one, but may not equal this value for two reasons. First, the selection of the missed and false alarm probabilities α and β will directly affect how many samples are required for a decision (refer to Equations (4-6a) and (4-6b)). Smaller values for the missed and false alarm probabilities necessarily require more samples on which to make a decision. Second, a sensor that is experiencing a bias drift affects the process variable estimate. Until the drift becomes large enough to be excluded from the estimate, it will bias the estimate, and therefore the values for MSTDN (and MSTDD). Thus the nominal value of MSTDN for a calibrated sensor may not be equal to one. On the other hand, the ideal value for the MSTDD (in the limit) is ∞. The selection of α and β will not affect the MSTDD for a normal sensor, since the value of Λ_n in Equation (4-10) will still trend toward the normal limit. For practical reasons (i.e., division by zero), the nominal value of MSTDD for a calibrated sensor will be represented by a "-1".

5.4 Sensor Adequacy Using Fuzzy Membership Functions

In section 5.2, we introduced the fuzzy membership functions that are used to index a set of performance characteristics. Section 5.3 described the set of performance characteristics of interest. In this section, the parameters that define the shape of the membership functions will be described using the allowable tolerance. The objective of this analysis is to provide an index of performance relative to a calibrated baseline for a given type of sensor. The index should be reproducible over a range of process variable conditions (i.e., over the sensor's range), providing that steady-state conditions exist.

In Table 5.2, the performance characteristics of interest are listed with the fuzzy membership functions, and the associated parameters (i.e., the peak point p and the bandwidth β) that define the shape of these functions. The intent is to base the parameters on the expected value and tolerance for each of the performance characteristics. Thus the peak point p is set equal to the expected value of the performance characteristic, and the bandwidth β corresponds to the desired tolerance. To allow the analyst to judge values outside the maximum allowable tolerance, the bandwidth of a membership function will be scaled such that its value is 0.5 (i.e., the *crossover point*) at the maximum allowable value of the parameter. For example, the peak point for the BIAS parameter is set to zero, the expected value for the sensor bias from the process variable estimate. The bandwidth is chosen to be equal to 3σ, which

Table 5.2 Membership Functions for Performance Characteristics

Parameter	Membership Function	Peakpoint	Bandwidth	Comments
BIAS	π - number	0	3σ	a
SII	z - number	0	N-1	b
MSTDN	z - number	1	12	c
MSTDD	z - number	1	12	c

Notes:

a. The value of σ is for the calibrated sensor. This choice of bandwidth is equal to the tolerance used in the GCC algorithm to generate the process variable estimate.

b. N is equal to the level of sensor redundancy.

c. The bandwidth was chosen based in the narrow region at which the MSTDN is approximately equal to the MSTDD. This corresponds to the state where the distribution of sensor measurements is approximately half way between the distributions for H0 and H1 .

corresponds to the maximum allowable tolerance used in the previous examples. For the π-number, this corresponds to a membership function value of 0.5. For the sensor inconsistency index, the peak point is also set to zero (the expected number of inconsistencies for a calibrated sensor). The bandwidth is set to the maximum possible value of N-1. Thus the crossover point occurs at a state where, relative to a particular sensor, approximately one half of the pairs of measurements are inconsistent (at this point, it is not clear if the sensor of interest is acceptable).

In the case of the MSTDN and the MSTDD, the choice for a peak point is the expected value for n in the SPRT (Equation (4-14)). If the distribution of a sensor's measurements were identical to the hypothetical normal distribution H_0 (for the MSTDN)

or the hypothetical abnormal distribution H_1 (for the MSTDD), then the value of n would be equal to one. Note that the peak point of the MSTDD is determined, for the case of a completely abnormal sensor, to have a membership function equal to one. For this parameter, complete membership corresponds to complete failure. However, a membership function value of zero does not imply a normal sensor. The membership function of the MSTDN equal to one corresponds to a completely normal sensor. Thus the MSTDD provides a measure of the degree of degradation, and the MSTDN provides a measure of the degree of normalcy, of a sensor. The determination of a value for the bandwidth is a bit more complicated. In the limit, the maximum value of the MSTDN or the MSTDD approaches infinity. A real maximum value may be equal to S, the size of the sample space. Using S, however, leaves a scale which is useless unless the sample space is small. To help select the bandwidth, let us examine the behavior of the MSTDN and the MSTDD for our artificial sensor example. Figure 5.3 shows the MSTDN and the MSTDD at some discrete values of error added to sensor #4. As previously demonstrated, when the bias error of sensor #4 increases, the value of the MSTDN increases, and the value of the MSTDD decreases. Note that there is a small region around an error of 0.4% at which the MSTDN and the MSTDD are approximately equal. In this region, the sensor is declared normal about half of the time, and abnormal the other half of the time. Therefore the results of the SPRT are inconclusive in this region. This corresponds to a sensor distribution that lies about half way between the distributions for H_0 and H_1 . This is a reasonable value to use for defining the crossover point, and therefore the bandwidth. The corresponding value of the MSTDN (and the MSTDD) of

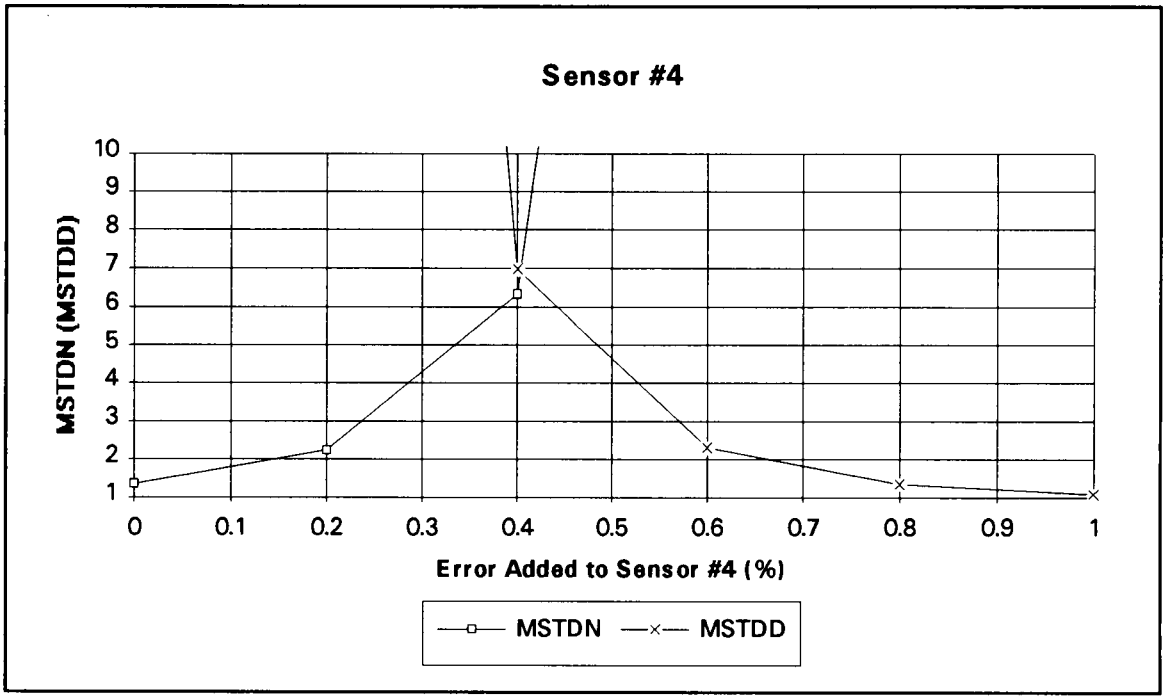
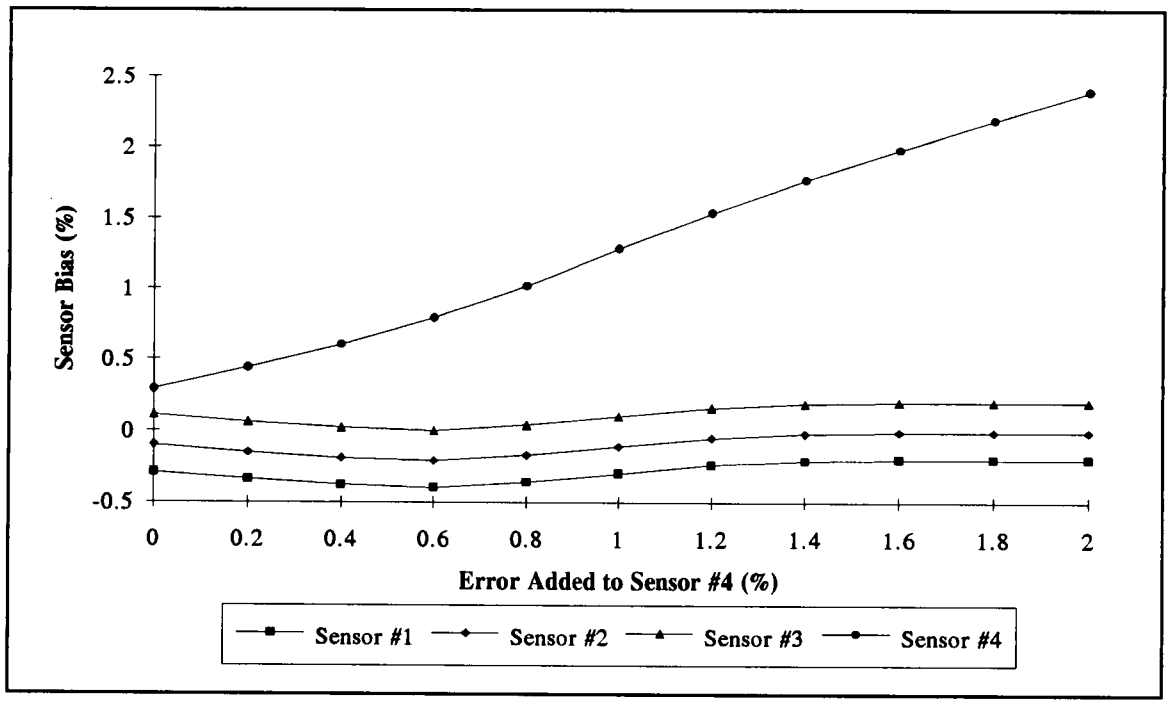


Figure 5.3 Behavior of the MSTDN and the MSTDD for the Example of Four Artificial Sensors.

approximately 6 for the crossover point gives a value of 12 for the bandwidth. The interpretation of this selection is that if less than six samples are required for the SPRT to reach a decision, then the test is conclusive for H_0 (or H_1) . It is noted that the actual value of n is a function of the false and missed alarm probabilities (α and β), the assumed variance of the distributions, and the maximum allowable bias, μ_1 . Thus the value of the bandwidth is sensor specific, and must be associated with the values of the above parameters that are used. For a particular set of sensors, the bandwidth will be determined empirically from the normal (calibrated) sensor behavior.

As an example, we will apply the membership functions to the artificial data example. Figures 5.4 through 5.7 illustrate the relationship between the sensor bias, SII, MSTDN, and MSTDD, and their respective membership functions. The top portion of each figure shows the behavior of the performance indicator as a function of the bias error added to sensor #4 (the faulted sensor). The bottom portion of each figure shows the corresponding index for each performance indicator, as quantified using the fuzzy membership functions discussed in this chapter, and the parameters given in Table (5.2).



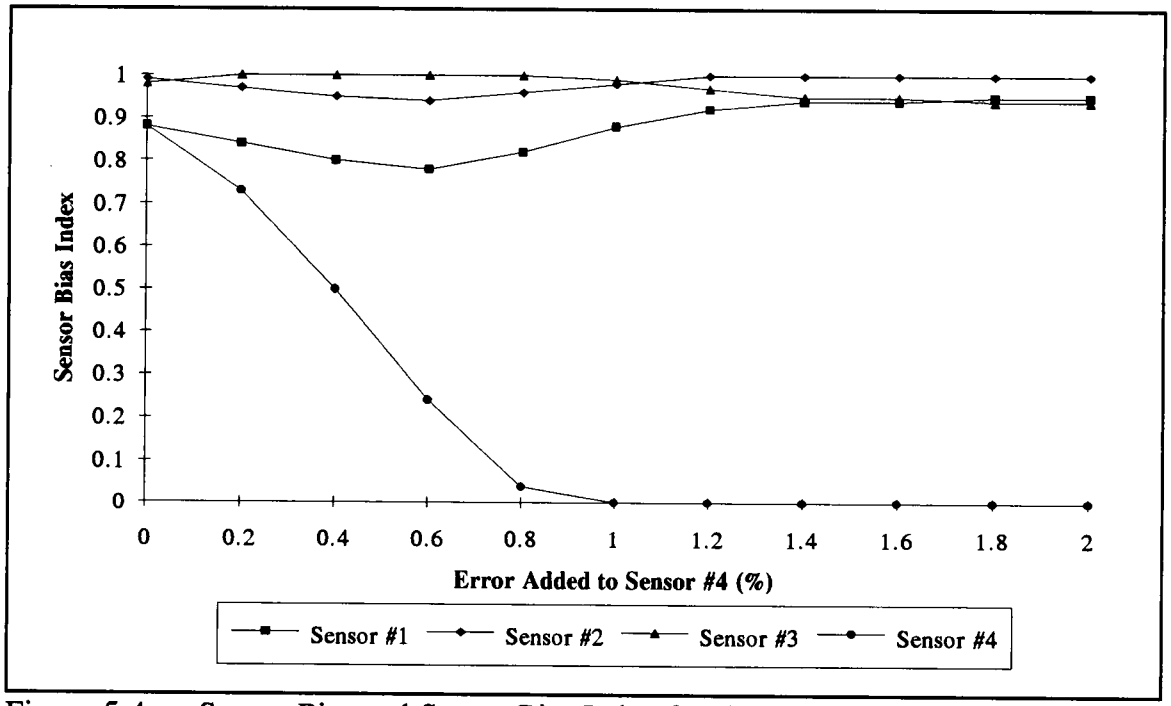
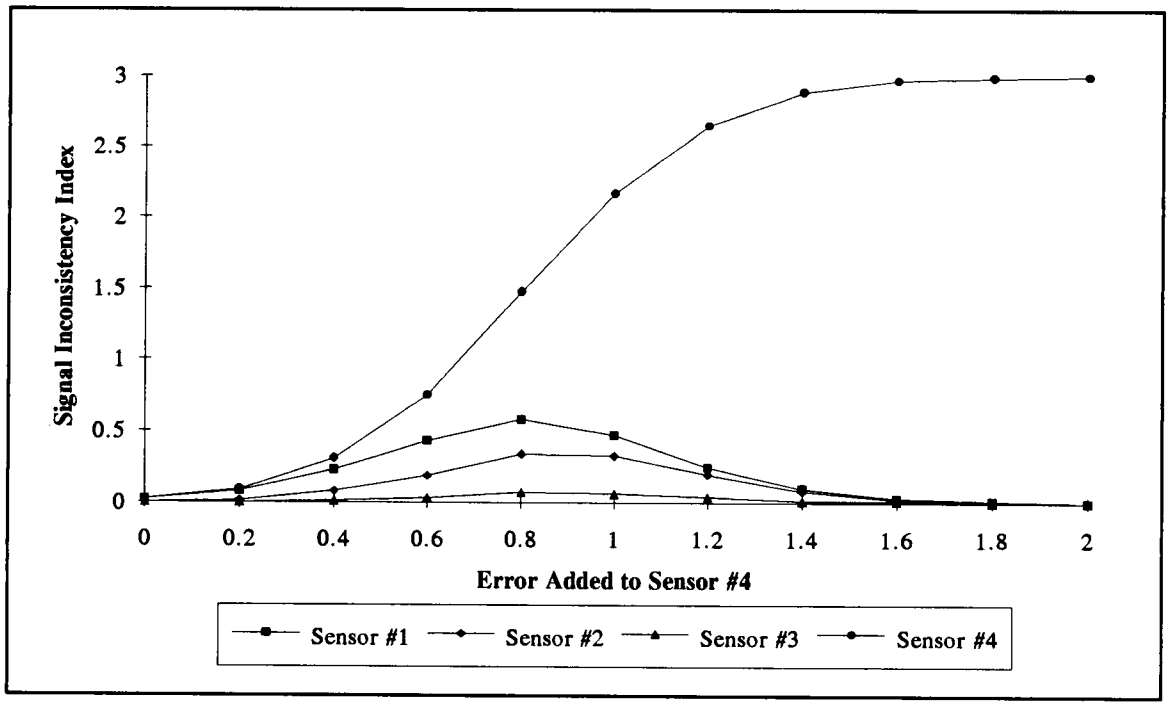


Figure 5.4 Sensor Bias and Sensor Bias Index for the Artificial Sensor Case.



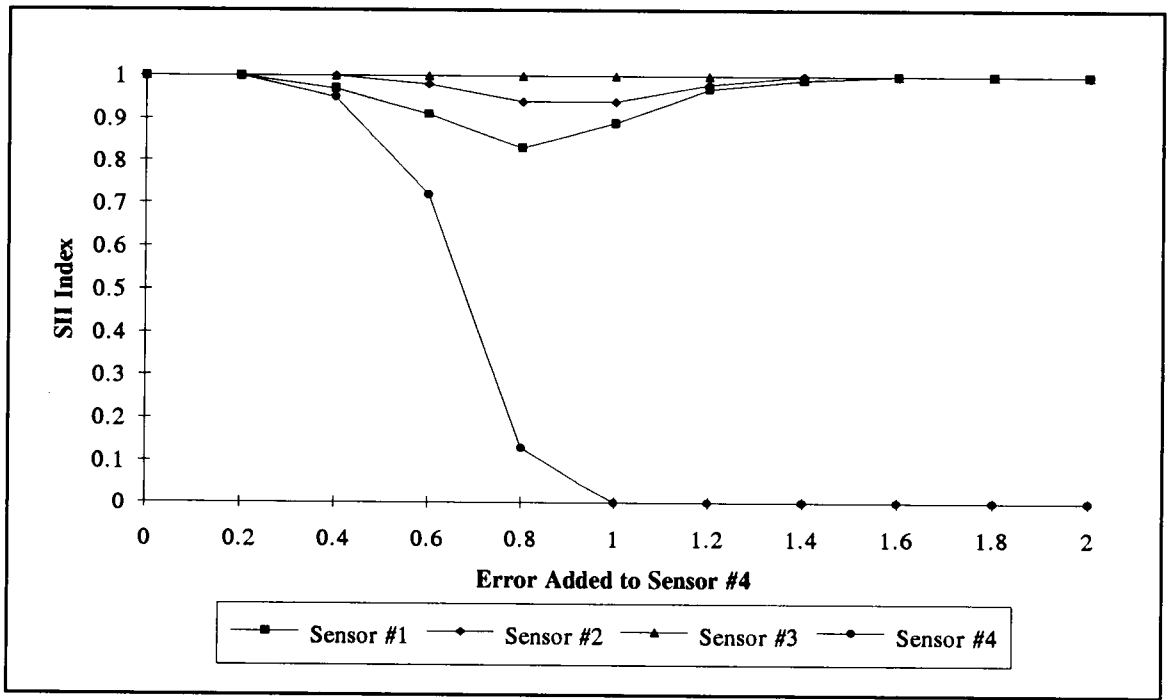
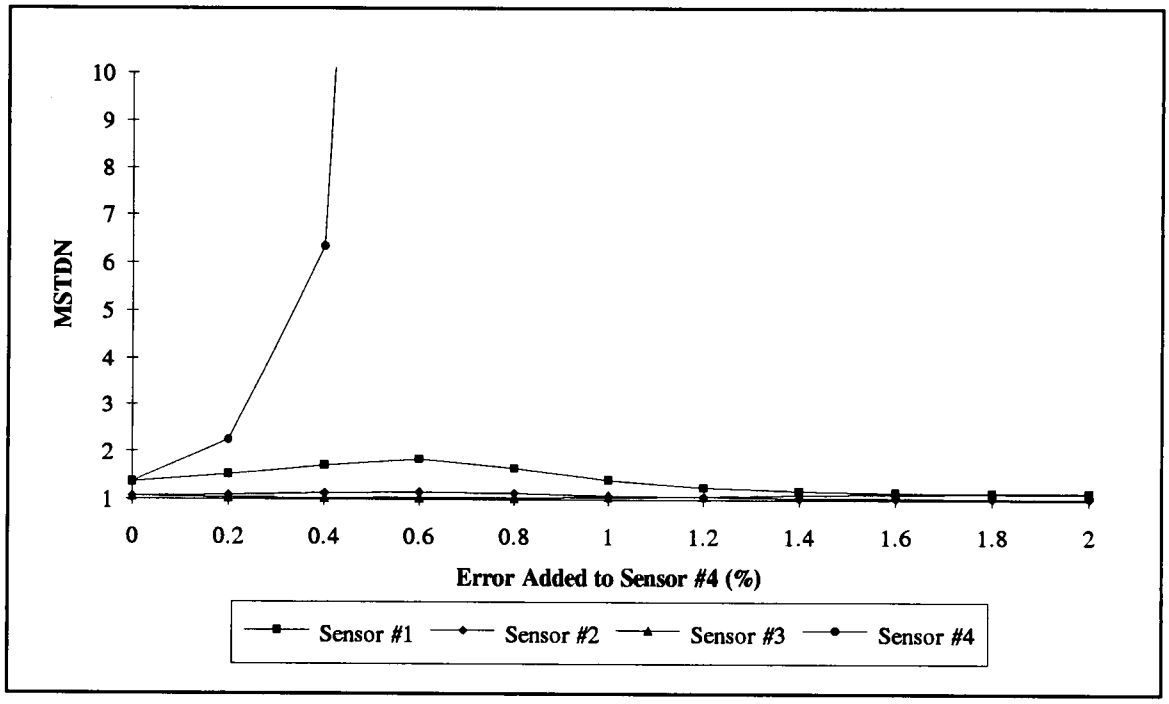


Figure 5.5 Signal Inconsistency Index (SII) and SII Index for the Artificial Sensor Case.



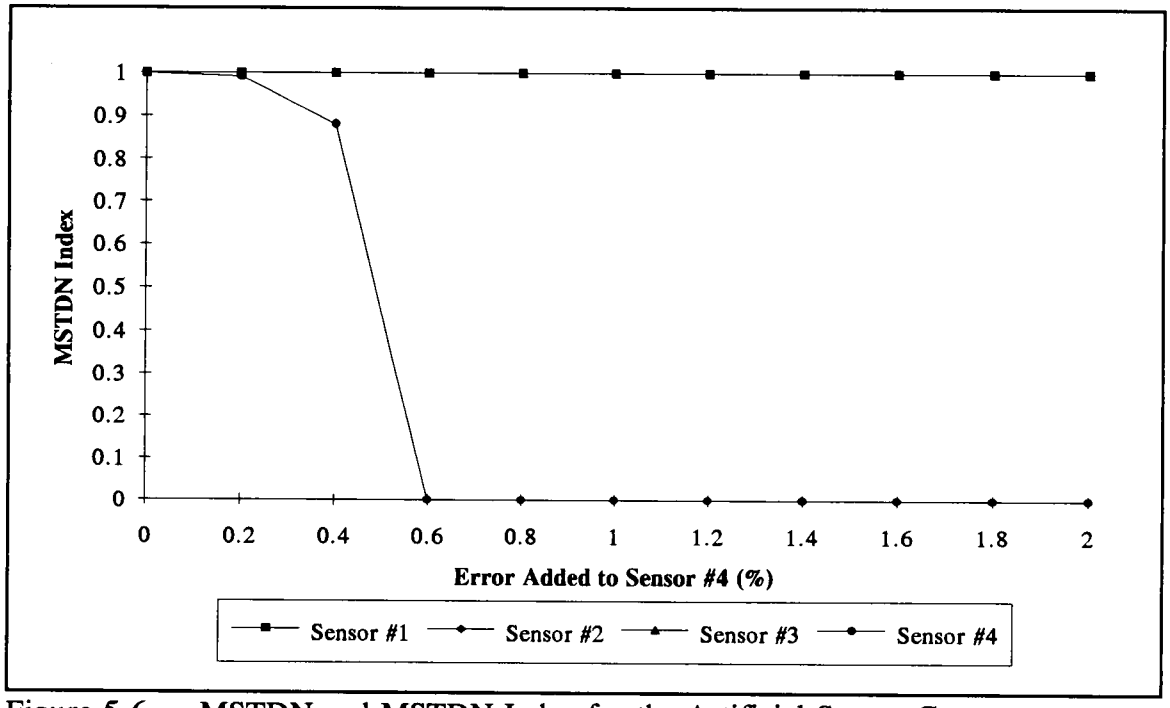
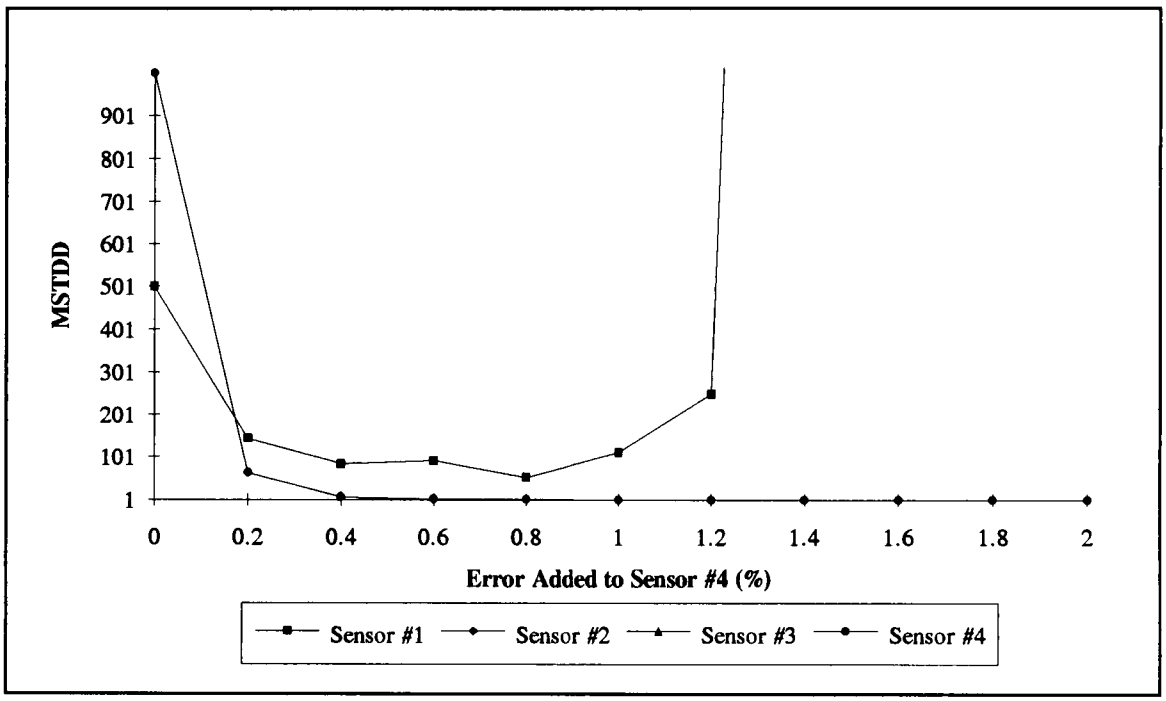


Figure 5.6 MSTDN and MSTDN Index for the Artificial Sensor Case.



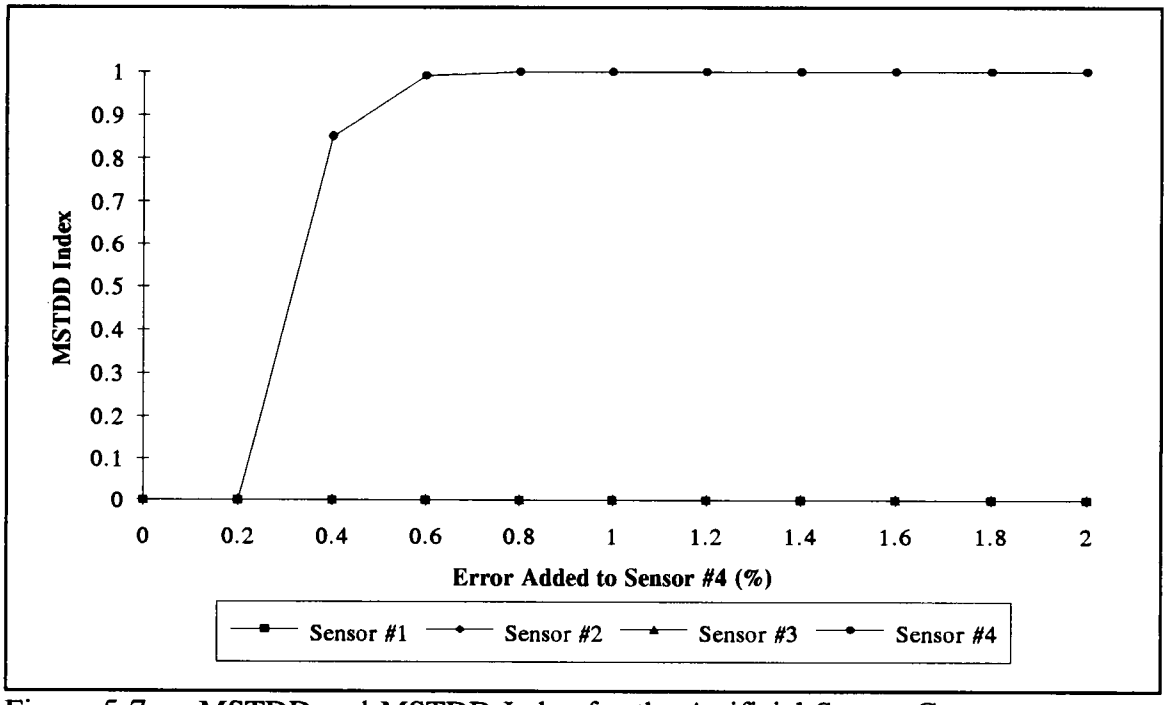


Figure 5.7 MSTDD and MSTDD Index for the Artificial Sensor Case.

6. APPLICATION OF THE METHODOLOGY

6.1 Description of Sensor Data

The Instrument Calibration Verification System (ICVS) was tested using an artificial data set (referred to as the "artificial data") and a real set of sensor data from a Westinghouse four-loop pressurized water reactor (referred to as the "PWR data"). The artificial data consists of four symmetrically spaced "sensors" created with a random number generator to represent a Gaussian distribution. The symmetric distributions were chosen to clearly demonstrate the effect of a faulted sensor on the behavior of all sensors. To simulate a faulted sensor for the examples presented in this thesis, the fourth sensor was perturbed by adding a bias error ranging from 0 to 2 percent. Table 6.1 lists the sensor statistics of the normal artificial data in terms of hypothetical "units". The results obtained using the artificial data are presented throughout the body of the thesis, and will not be reproduced in this chapter. The PWR data were obtained from a steady-

Table 6.1 Sensor Statistics for the Artificial Data.

Sensor #	Mean	Std. Deviation	Skewness	Kurtosis
1	99.7	0.20	-0.09	1.02
2	99.9	0.20	0.05	1.00
3	100.1	0.20	0.02	0.98
4	100.3	0.20	0.01	1.06

state run using a sampling interval of 30 seconds. The data consist of 132 channels, and includes temperature, pressure, flow, and power measurements for the Reactor Coolant System (RCS) and selected associated systems.

To demonstrate the ICVS, we chose the neutron power range monitors as the process variable of interest. The power range monitoring system consists of four monitoring tubes located at 0, 90, 180, and 360 degrees around the outside of the vessel. The scaled output for the monitors is expressed as a percent of full reactor power, from zero to 100 percent. Figure 6.1 shows the time behavior of one channel of the neutron power range monitor. Table 6.2 lists the sensor statistics of the neutron monitors for this particular set of data. The skewness and kurtosis provide a measure of how well the data are represented by a Gaussian distribution. All sensors appear to have a good fit, with sensor NPRM-1 having the flattest distribution, and sensor NPRM-4 having the largest skew. Figure 6.2 illustrates the frequency histograms for all of the sensors compared to the ideal Gaussian distributions having the same mean and variance as the sensors.

Table 6.2 Sensor Statistics for the Neutron Power Range Monitors.

Sensor ID	Mean	Std. Deviation	Skewness	Kurtosis
NPRM-1	99.2	0.22	-0.11	0.93
NPRM-2	99.3	0.25	-0.01	0.99
NPRM-3	98.9	0.25	0.00	0.99
NPRM-4	99.4	0.26	-0.23	1.02

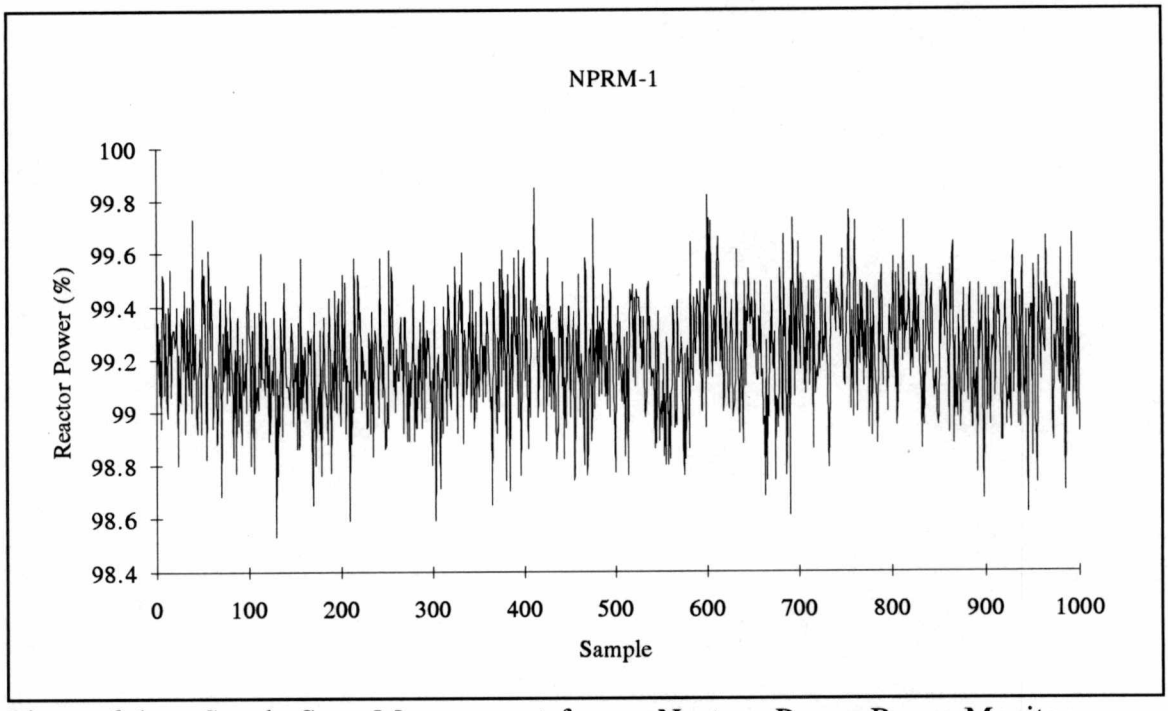
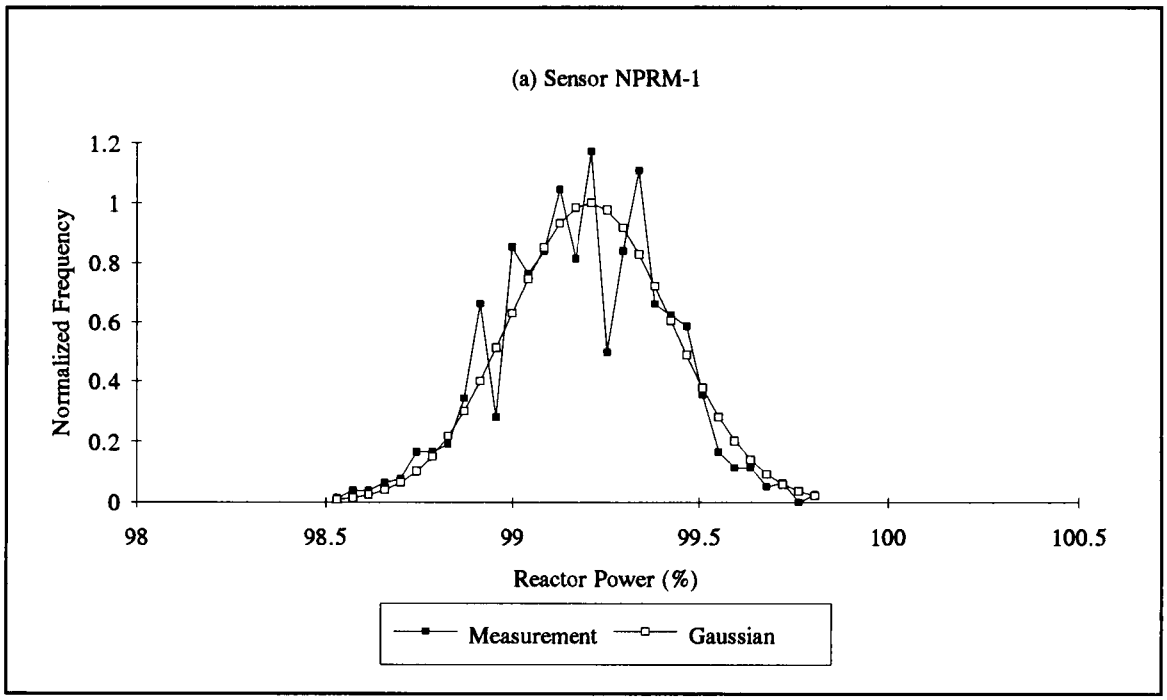


Figure 6.1 Steady-State Measurement from a Neutron Power Range Monitor.



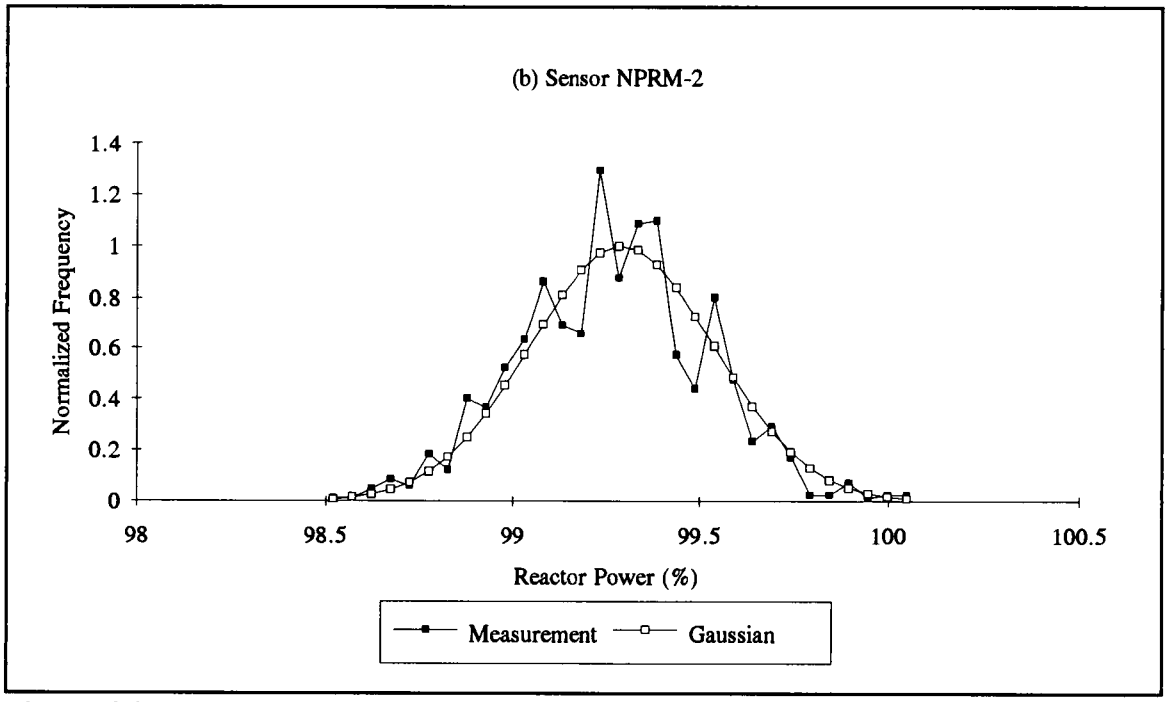
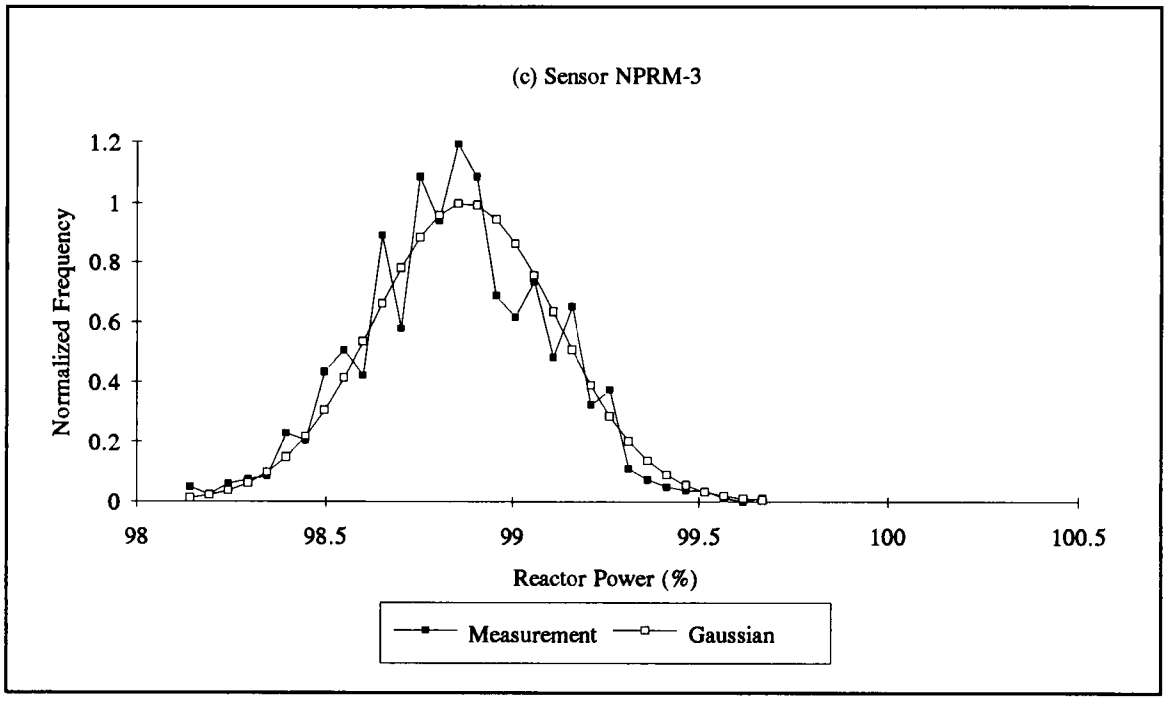


Figure 6.2 Normalized Frequency Histogram for Neutron Power Range Sensors.



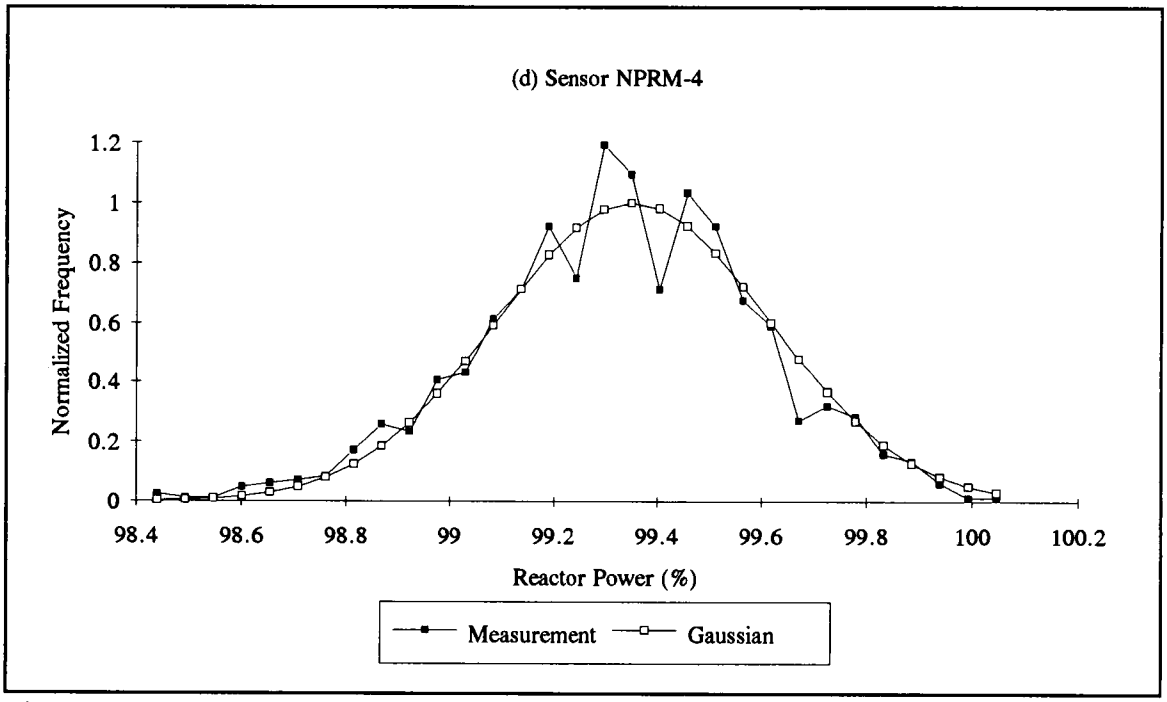


Figure 6.2 Normalized Frequency Histogram for Neutron Power Range Sensors (continued).

A transient data set taken during start-up is also used to create the PEM model. The start-up data span from zero to 100 percent of full power, and include many of the same channels as the steady-state data described above. The PEM model uses the reactor power as an output variable, and four other process variables as inputs. The input variables are (1) pressurizer level, (2) cold leg temperature, (3) hot leg temperature, and (4) main steam pressure. Using one channel from each group of sensors, all five variables are shown for the entire start-up range in Figures 6.3 through 6.7. To maximize the accuracy, the range of the data used to generate the model was limited to reactor power between 98 and 102 per cent of full scale. This is a good range for steady-state operation at full power. Models with narrow ranges can be generated at other useful power levels where power ascension may be halted for testing (e.g., a power plateau at 50% of full power is common). Larger ranges may be generated, but will also result in a larger error in the estimate. The reactor power model used in this thesis was presented in Figure 3.7.

The model that was generated using the start-up data was applied to the steady-state data to create the PEM estimate used by the GCC algorithm. Figure 6.8 shows the comparison of the PEM estimate with measurements from one of the neutron power range monitors. The mean value for the PEM estimate and the measurement shown in the figure is 99.36% and 99.21% respectively. Thus the PEM model provides a good estimate of this particular channel.

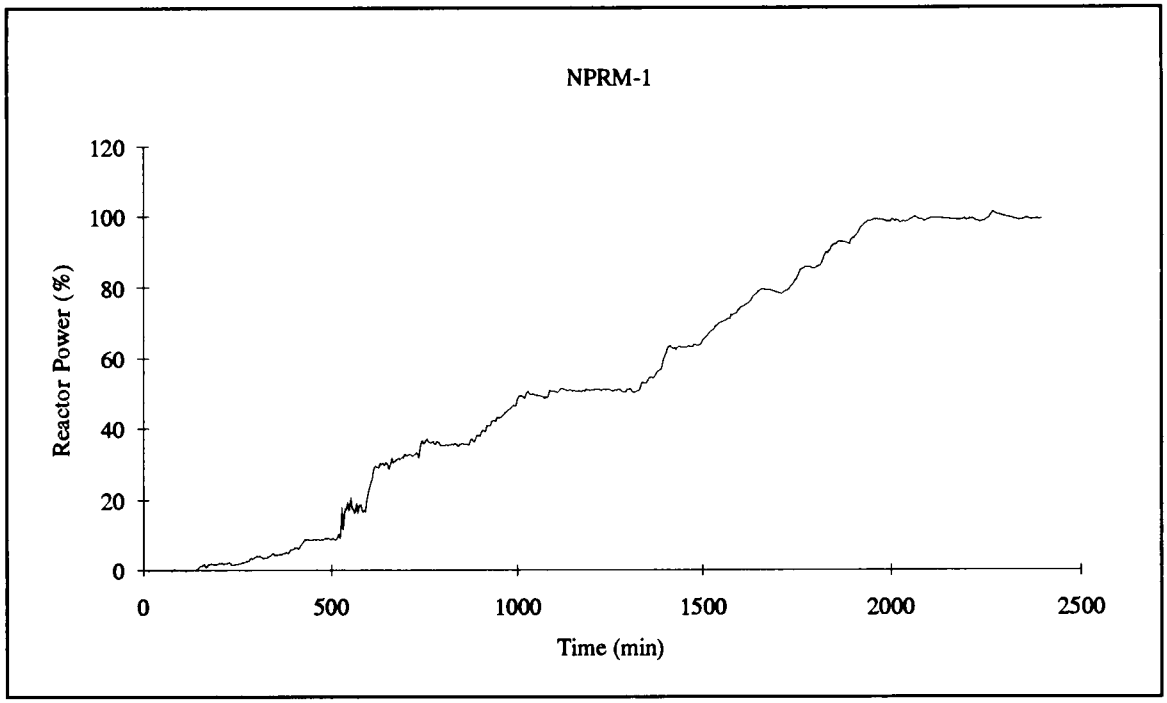


Figure 6.3 Reactor Power Data Used as the PEM Model Output.

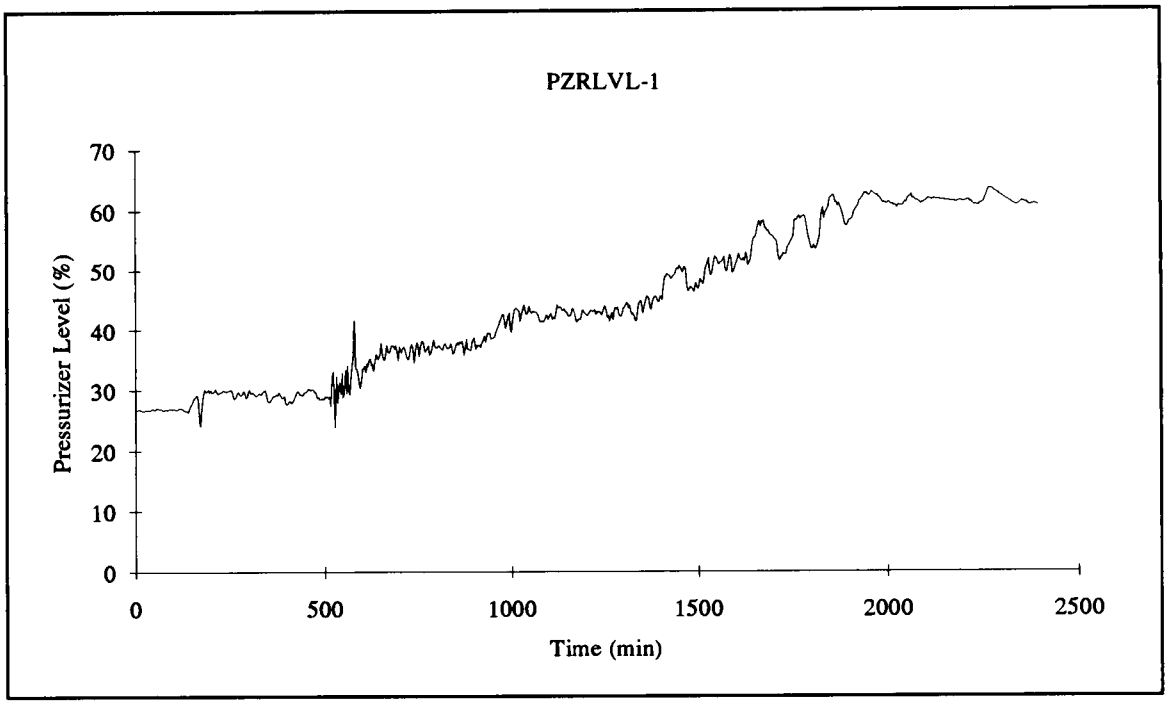


Figure 6.4 Pressurizer Level Data Used as a PEM Model Input.

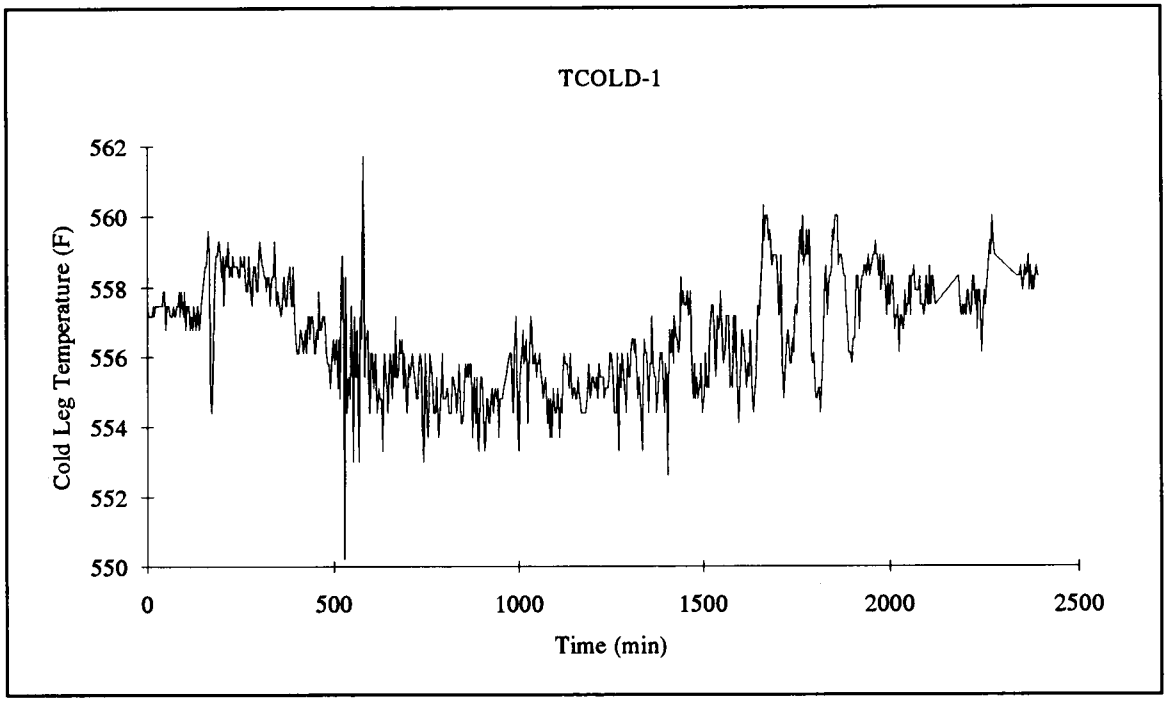


Figure 6.5 Cold Leg Temperature Data Used as a PEM Model Input.

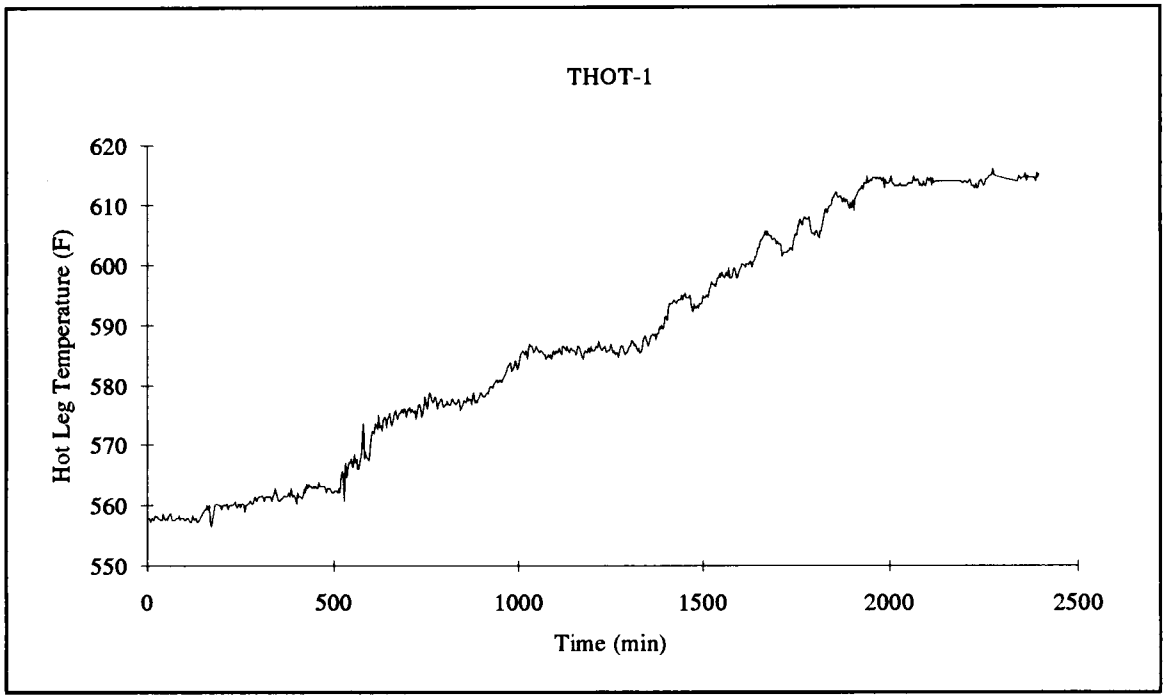


Figure 6.6 Hot Leg Temperature Data Used as a PEM Model Input.

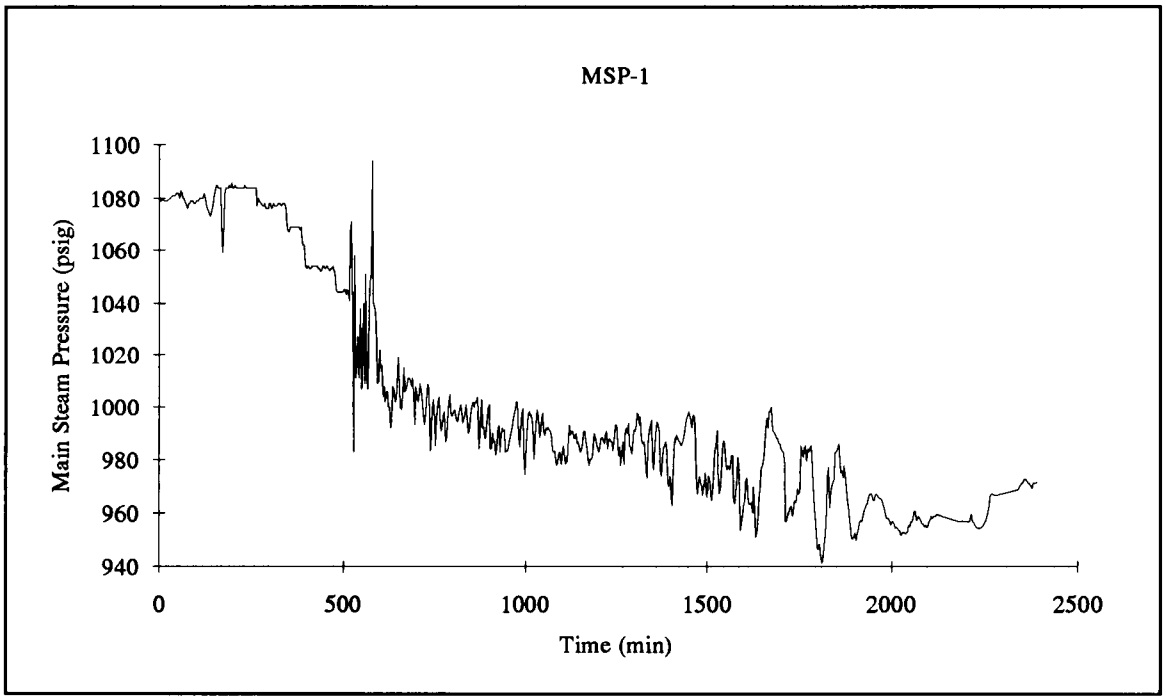


Figure 6.7 Main Steam Pressure Used as a PEM Model Input.

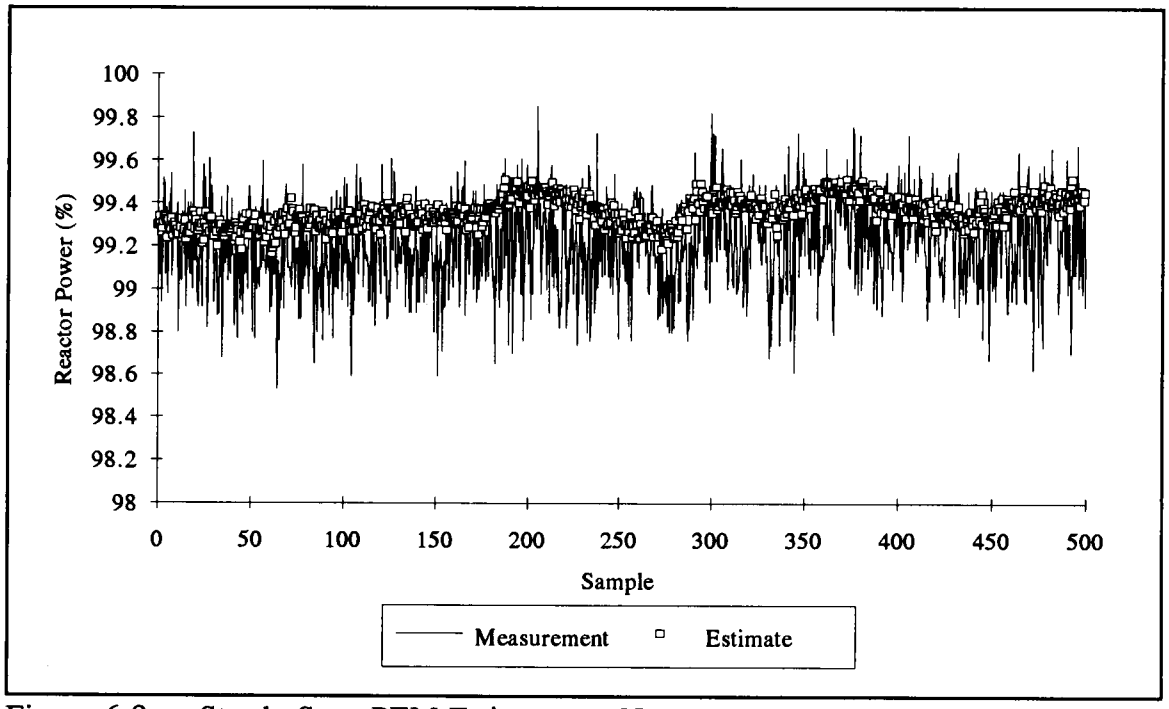


Figure 6.8 Steady State PEM Estimate vs. Neutron Power Range Monitor.

6.2 Description of the Test Cases

The steady-state PWR data are the basis for all of the test cases presented in this chapter. Since actual failure data is difficult to obtain, sensor errors are simulated by adding a bias to the steady-state data for a given sensor. Thus the sensor data were simply shifted up or down, and the noise characteristics of the sensors remain unchanged. The test cases are intended to demonstrate the effect that various sensor bias errors have on the performance indicators of the ICVS. The following discussion describes each test case, which are summarized in Table 6.3.

Case I - Base Case

The base case represents a set of normal, calibrated sensors. It provides the basis for the parameters that are used to run the ICVS such as the sensor tolerance for the GCC algorithm (b from Equation (3.1)) and the maximum allowable sensor bias (μ_1 from Equation (4-14)) and normal sensor variance for the SPRT. The base case and all test cases were analyzed with a sensor tolerance equal to three times the standard deviation of the sensor (this corresponds to a confidence of 99.7% for a Gaussian distribution). The maximum allowable sensor bias were set at six times the standard deviation of the sensor. This sets the probabilities of missed and false alarms equal to approximately 0.0015, based on a critical point y_c set at the intersection of the normal and faulted distributions (see Figure 4.3). Using the normal sensor statistics given in Table 6.2 for

Table 6.3 Summary of Test Cases for the ICVS.

Case No.	Description
I	Base case. All sensors are considered to be calibrated.
II	Single sensor error. Bias error equals +1% on sensor NPRM-1.
III	Single sensor error. Bias error equals +2% on sensor NPRM-1.
IV	Single sensor error. Bias error is ramped from 0% to 2% on sensor NPRM-1.
V	Two sensor error. Bias error equals +1% on sensors NPRM-1 and NPRM-2.
VI	Two sensor error. Bias error equals +1% on sensor NPRM-1 and -1% on sensor NPRM-2.
VII	Common cause failure. Bias error equals +1% on all four sensors.

the neutron power range monitors, the resulting inputs for the ICVS are given in Table 6.4. Note that the typical tolerance allowed in plant technical specifications for the neutron power range monitors are on the order of ±2% of full scale. Thus the tolerances listed in Table 6.4 are well within the allowable limits.

Case II - Single Sensor Error (1%)

Case II represents a single sensor (NPRM-1) that has experienced a bias drift of +1% of full scale. The sensor bias drift is a deviation from nominal (base case) conditions, but is still considered to be within normal limits. This case demonstrates the ability of the ICVS to measure changes in a sensor's characteristics from the calibrated state.

Case III - Single Sensor Error (2%)

Case III represents a single sensor error (NPRM-1) that has experienced a bias drift of +2% of full scale. The sensor bias drift has exceeded acceptable limits, and is considered to be out of calibration. This case demonstrates the ability of the ICVS to (1) measure changes in a sensor's characteristics from the calibrated state, (2) indicate a completely degraded sensor with respect to bias drift and, (3) reject a sensor with an unacceptable bias drift from the process variable estimation.

Table 6.4 ICVS Input Parameters for the All Test Cases.

Sensor ID	Sensor tolerance (GCC)	Sensor bias (SPRT)	Variance
NPRM-1	0.66	1.3	0.05
NPRM-2	0.75	1.5	0.06
NPRM-3	0.75	1.5	0.06
NPRM-4	0.81	1.6	0.07

Case IV - Single Sensor Error (Bias Error Ramped form 0% to 2% of Full Power)

Case IV is presented to illustrate the behavior of the SPRT as a function of the bias drift of a single sensor. The behavior of the SPRT plot can trend changes in the sensor bias.

Case V - Two Sensor Error (+1%, +1%)

Case V represents two sensors (NPRM-1 and NPRM-2) that have both experienced a bias drift of +1% (i.e., in the same direction). This demonstrates the effect of a two sensor bias drift on the results of the ICVS. The intention is to illustrate a case where a decision on the calibration state of any sensor may not be possible.

Case VI - Two Sensor Error (+1%, -1%)

Case VI represents two sensors, NPRM-1 and NPRM-2, that have experienced bias drifts of +1% and -1% respectively (i.e., in the opposite direction). This demonstrates the effect of a two sensor bias drift on the results of the ICVS. The intent is to illustrate a case where a decision on the calibration state of any sensor may not be possible.

Case VII - Common Cause Failure

Case VII represents a common cause failure of all redundant sensors of +1%. A common cause failure of redundant sensors may occur for several reasons (procedural error, technician error, design flaw, external influence such as radio frequency noise, etc.). The intent is to show that the resulting disagreements that occur between the sensors and the PEM estimate alert the analyst to a potential problem. At this point it may not be possible to determine if the failure is a true common cause failure or a PEM estimate failure.

6.3 Results of the Test Cases

The results of the test cases are generated by a software system that was written for the ICVS. The ICVS software generates results in a tabular format, which is then imported to a spreadsheet for graphic generation. Appendix A presents a more detailed description of the ICVS software, and Appendix B provides a FORTRAN code listing of the software. The ICVS and spreadsheet are used to generate the following output

- a calibration verification summary
- a graph of process variable estimate
- graphs of the GCC results
- graphs of the SPRT results

The calibration verification summary is divided into four sections; (1) Signal Statistics, (2) Generalized Consistency Checking Results, (3) Sequential Probability Ratio Test Results and, (4) Estimate Mean. Section (1) summarizes the mean, standard deviation, skewness, and kurtosis for each sensor (and PEM estimate if required) over the entire analyzed sample space. Section (2) presents the mean values and performance indices for the sensor inconsistency index (SII) and the sensor bias (BIAS). Also listed in Section (2) is the percent of the total samples that a sensor was excluded from the GCC estimate (% EXCL). In Section (3), the values and performance indices of the SPRT parameters MSTDN and MSTDD are given. Note that to avoid division by zero in the computer

algorithm, a negative one is used for the MSTDN or MSTDD to denote a value of infinity. Section (4) contains the mean value of the GCC estimate over the entire sample space with the span of these values in parentheses.

The graphic outputs provide a visual look at the time dependent behavior of the GCC estimate, and of the consistency checking indices and SPRT results for each of the sensors over the entire sample space. Trends in sensor behavior can be qualitatively assessed using the graphic output.

The results for each case are presented in the following sections. The outputs described above are presented for each test case, along with a brief discussion of the results. Note that to limit repetitive information, only the SPRT graphs are provided for Case IV, and only the summary tables are provided for Cases V through VII.

Case I - Base Case

The results of Case I are shown in Table 6.5 and Figures 6.9 through 6.10. This case provides the base line analysis for the neutron power range monitors. The results are considered to represent the normal behavior for these sensors. Table 6.5 shows that the mean values for all of the sensors (including the PEM estimate) fall within a one-half percent span. The standard deviations for all of the sensors are very close, and the skewness and kurtosis indicate a fairly good fit to a Gaussian distribution (sensors 2 and

Table 6.5 ICVS Summary Results for Case I.

CALIBRATION VERIFICATION SUMMARY

	SIGNAL 1	SIGNAL 2	SIGNAL 3	SIGNAL 4	SIGNAL 5
Signal Statistics					
MEAN	99.21	99.29	98.87	99.35	99.00
STD DEV	.22	.25	.25	.26	.25
SKEWNESS	-.11	-.01	.00	-.23	-.01
KURTOSIS	.93	.99	.99	1.02	.87
Generalized Consistency Checking Results					
% EXCL	.00	.00	.00	.00	.00
SII	.00	.00	.00	.00	.00
BIAS	.06	.15	-.27	.21	-.15
SII INDEX	1.00	1.00	1.00	1.00	1.00
BIAS INDEX	1.00	.98	.93	.96	.98
Sequential Probability Ratio Test Results					
MSTD NORM	1.02	1.05	1.16	1.07	1.07
MSTD DEGR	-1.00	-1.00	-1.00	-1.00	-1.00
NORM INDEX	1.00	1.00	1.00	1.00	1.00
DEGR INDEX	.00	.00	.00	.00	.00

ESTIMATE MEAN = 99.14

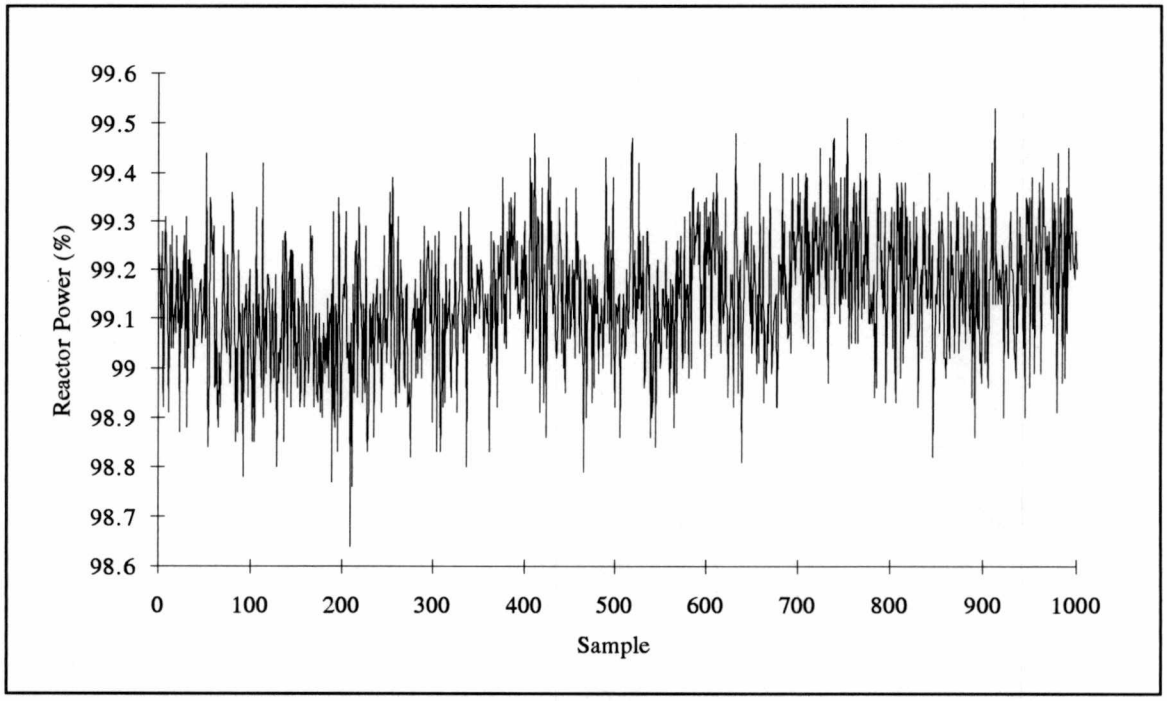
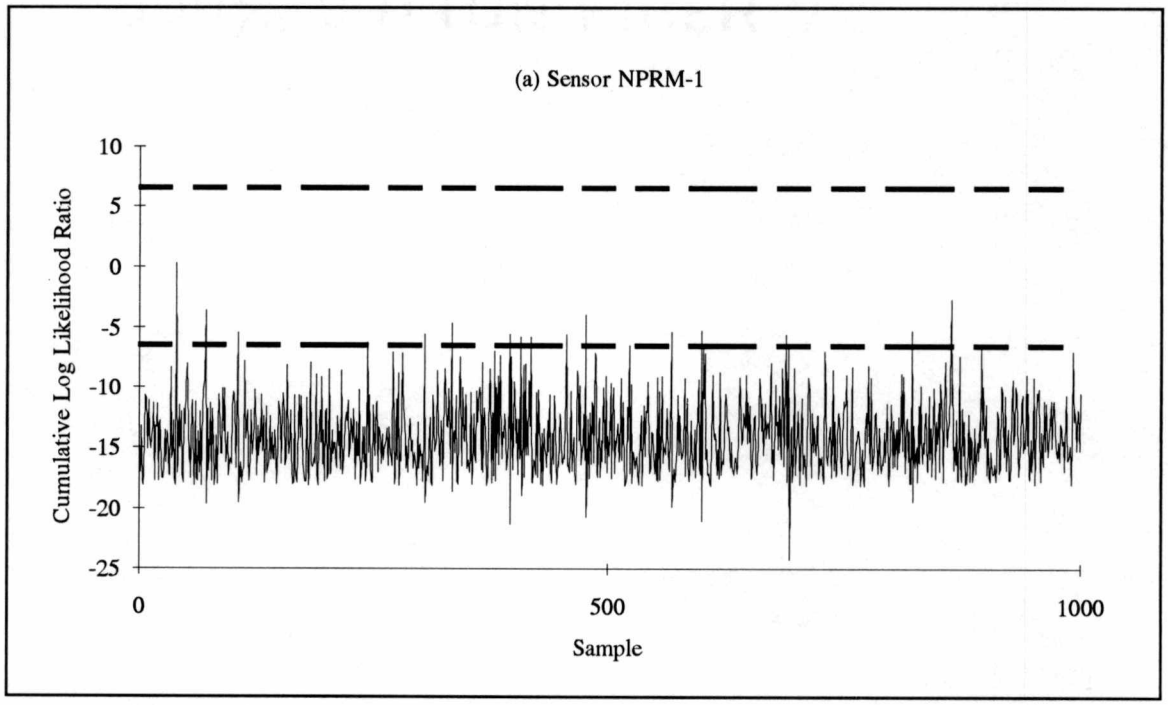


Figure 6.9 GCC Estimate for Case I.



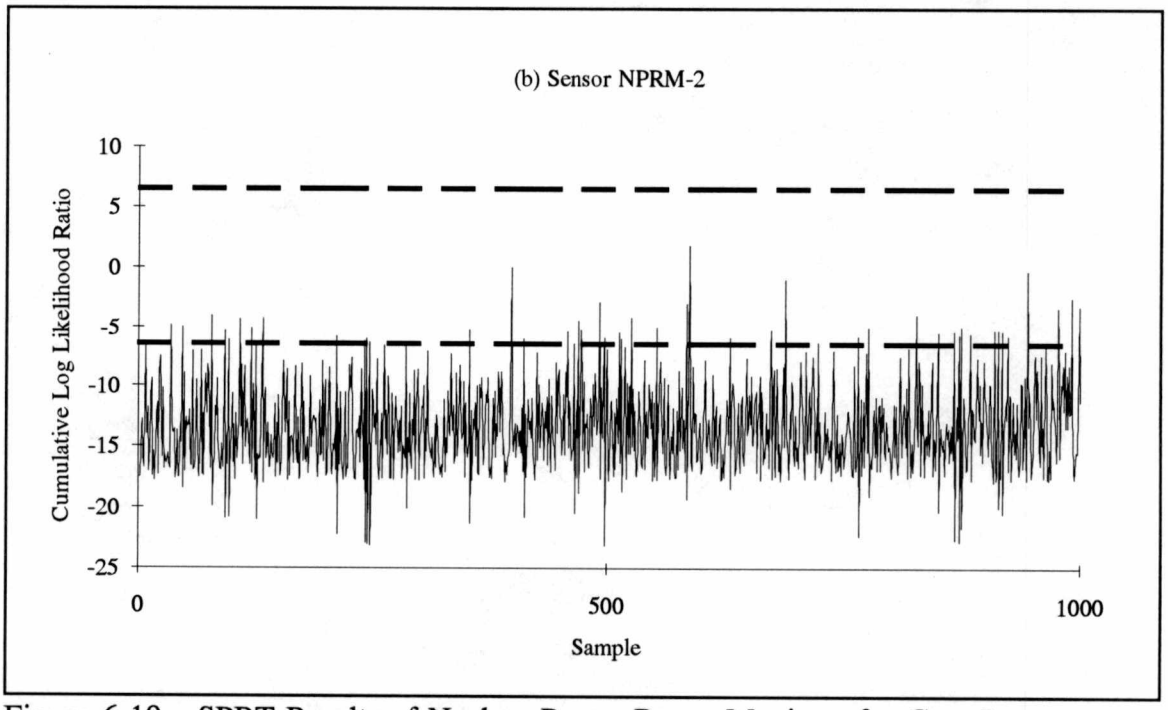
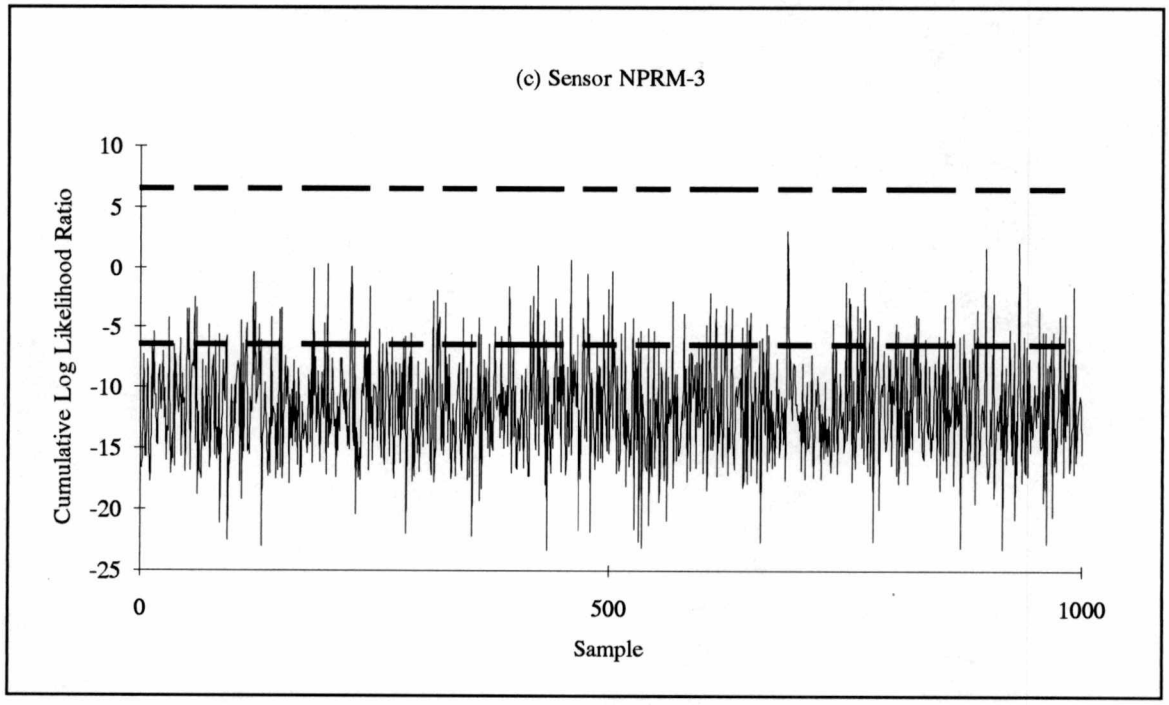


Figure 6.10 SPRT Results of Nuclear Power Range Monitors for Case I.



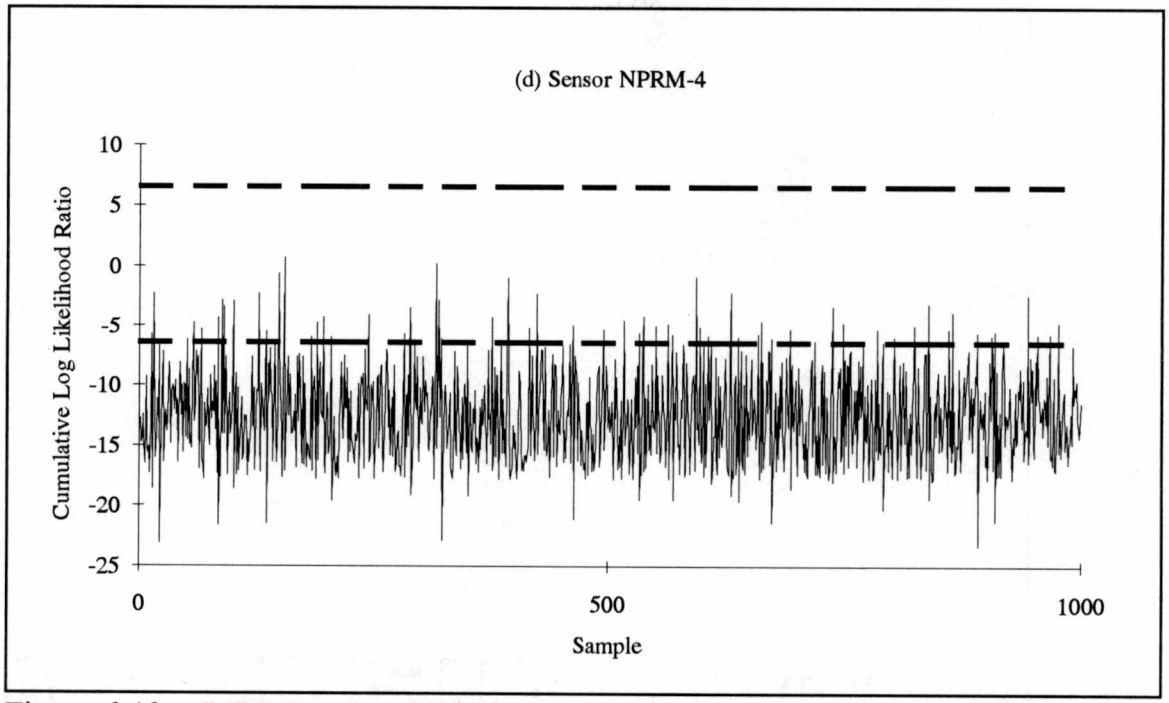


Figure 6.10 SPRT Results of Nuclear Power Range Monitors for Case I (continued).

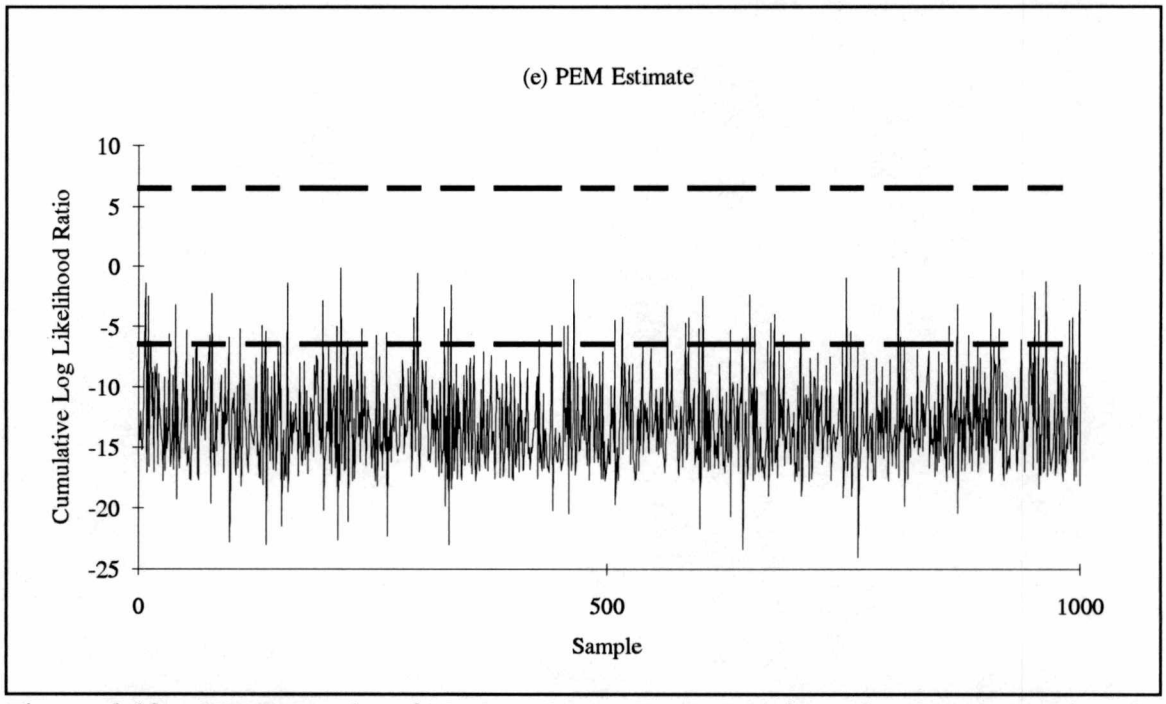


Figure 6.10 SPRT Results of Nuclear Power Range Monitors for Case I (continued).

3 having the closest fit). The results of the base case analysis give the normal values for the GCC and SPRT results for these particular sensors. The sensor inconsistency indices are all equal to zero (with corresponding performance indices equal to one), indicating no inconsistent pairs. As expected, there is a small bias associated with each sensor. The important result is that the biases are small; the largest being approximately one standard deviation in magnitude, well within the tolerace of three standard deviations used for all of the test cases. Note that the bias indices are less than one (but still well above 0.5) for four out of five of the sensors. This is a result of the bandwidth chosen for the fuzzy membership function for this index (a value of 0.5 corresponds to a bias of approximately 3σ). The SPRT results show values of the MSTDN slightly greater than the ideal value of one (with a normal index of 1.0 for all sensors), and values of the MSTDD of infinity (with a degraded index of 0 for all sensors). This indicates that the outcome of all SPRT decisions in this sample space is normal. The values for the sensor MSTDN shows that usually one sample was required to achieve a normal decision. Finally, the mean GCC estimate is shown to be 99.14%. Since the percent of samples excluded from the GCC estimate is zero for all sensors, this value is just equal to the average of the mean values for the five signals.

Figures 6.9 and 6.10 show the time dependent behavior for the results presented above. The GCC estimate shows some small variation over time. This is due to the variations that occur during steady-state conditions in the plant. The consistency checking results were not presented for Case I since there were no inconsistent pairs. The SPRT

plots show that the cumulative log likelihood ratio never crosses the degraded (upper) limit, although it does become positive for a couple of samples. For most of the samples, the value of the log likelihood ratio is below the normal (lower) limit, and is then reset to zero for the next decision cycle.

The Case I results indicate a set of normal, calibrated sensors. Thus these results provide a good baseline for comparison with additional analysis of degrading sensors.

Case II - Single Sensor Error (1%)

The results of Case II are shown in Table 6.6 and Figures 6.11 through 6.13. This case illustrates the effect on the ICVS results of a single sensor (NPRM-1) with a one percent bias degradation. A one percent bias degradation represents a sensor which is within its allowable tolerance and is therefore not clearly out of calibration. Table 6.6 shows that NPRM-1 (labeled as signal 1) has a sensor inconsistency index of 0.74 and a bias of 0.89%. While this is a change from the baseline results, it is not clear which sensor(s) are responsible for the differences. This is because the SII and bias of the other sensors have also changed, most notably NPRM-3 (signal 3). This is an expected result since the bias degradation of NPRM-1 is not severe enough to exclude it from the GCC estimate (from Table 6.6, it was excluded 0.1% of the time), thus allowing NPRM-1 to bias the GCC estimate and change the results for all of the sensors (the GCC estimate is 99.14% for Case I and 99.32% for Case II). The SII and bias indices provide a clearer

Table 6.6 ICVS Summary for Case II.

CALIBRATION VERIFICATION SUMMARY

	SIGNAL 1	SIGNAL 2	SIGNAL 3	SIGNAL 4	SIGNAL 5
Signal Statistics					
MEAN	100.21	99.29	98.87	99.35	99.00
STD DEV	.22	.25	.25	.26	.25
SKEWNESS	-.11	-.01	.00	-.23	-.01
KURTOSIS	.93	.99	.99	1.02	.87
Generalized Consistency Checking Results					
% EXCL	.10	.00	.00	.00	.00
SII	.74	.05	.39	.02	.28
BIAS	.89	-.03	-.45	.03	-.32
SII INDEX	.73	1.00	.93	1.00	.96
BIAS INDEX	.22	1.00	.82	1.00	.91
Sequential Probability Ratio Test Results					
MSTD NORM	125.00	1.01	1.58	1.03	1.27
MSTD DEGR	1.89	-1.00	500.00	-1.00	-1.00
NORM INDEX	.00	1.00	1.00	1.00	1.00
DEGR INDEX	1.00	.00	.00	.00	.00

ESTIMATE MEAN = 99.32

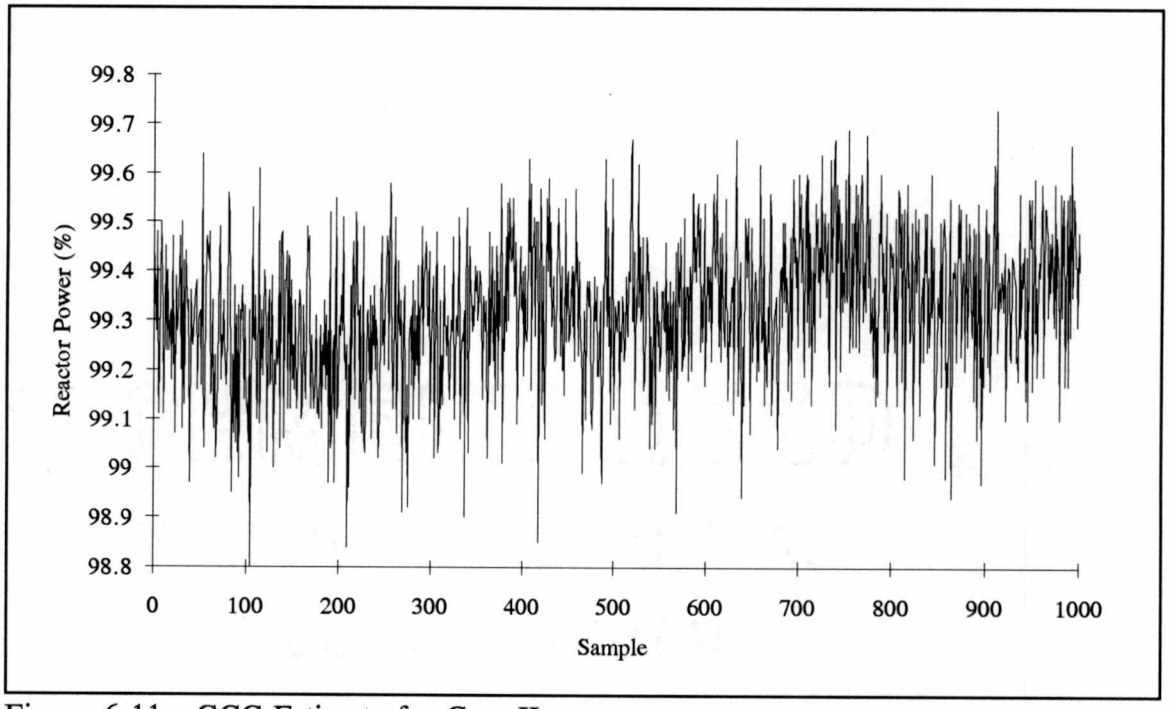
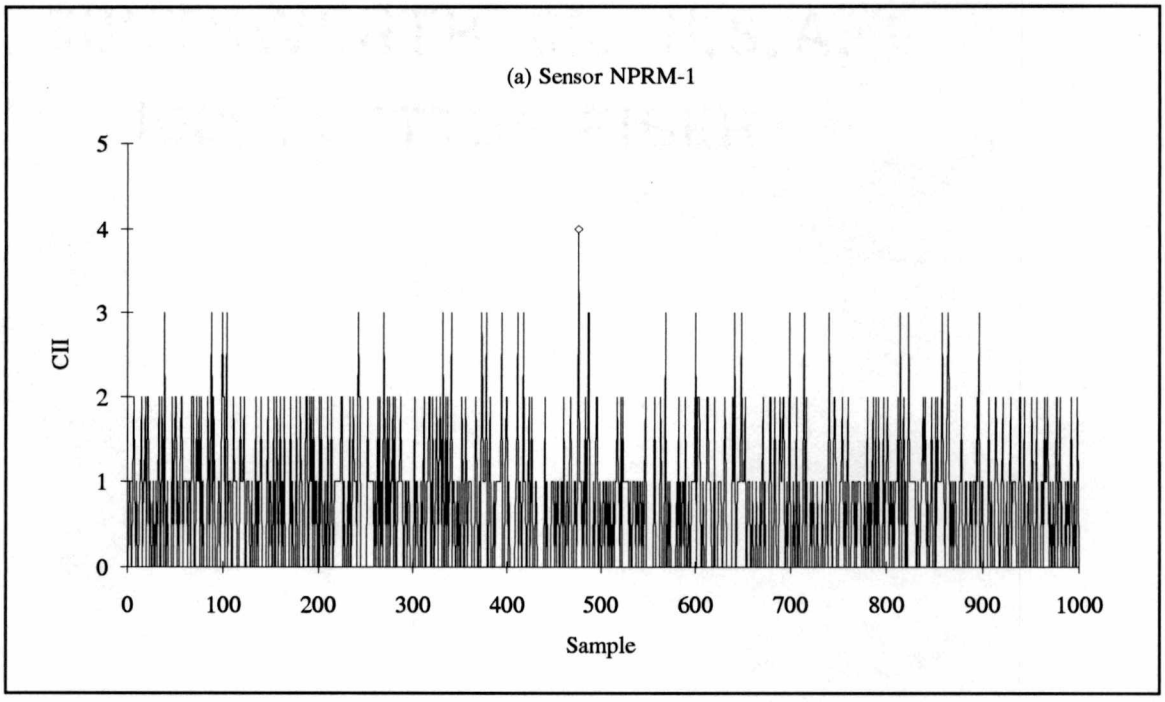


Figure 6.11 GCC Estimate for Case II.



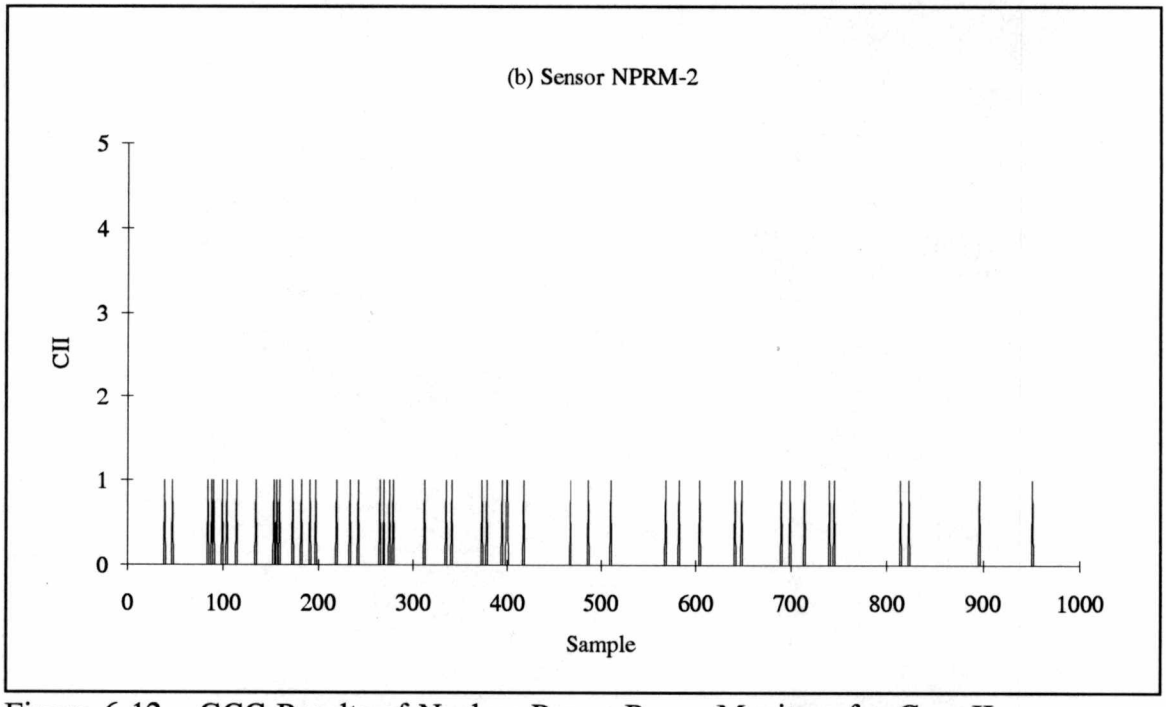
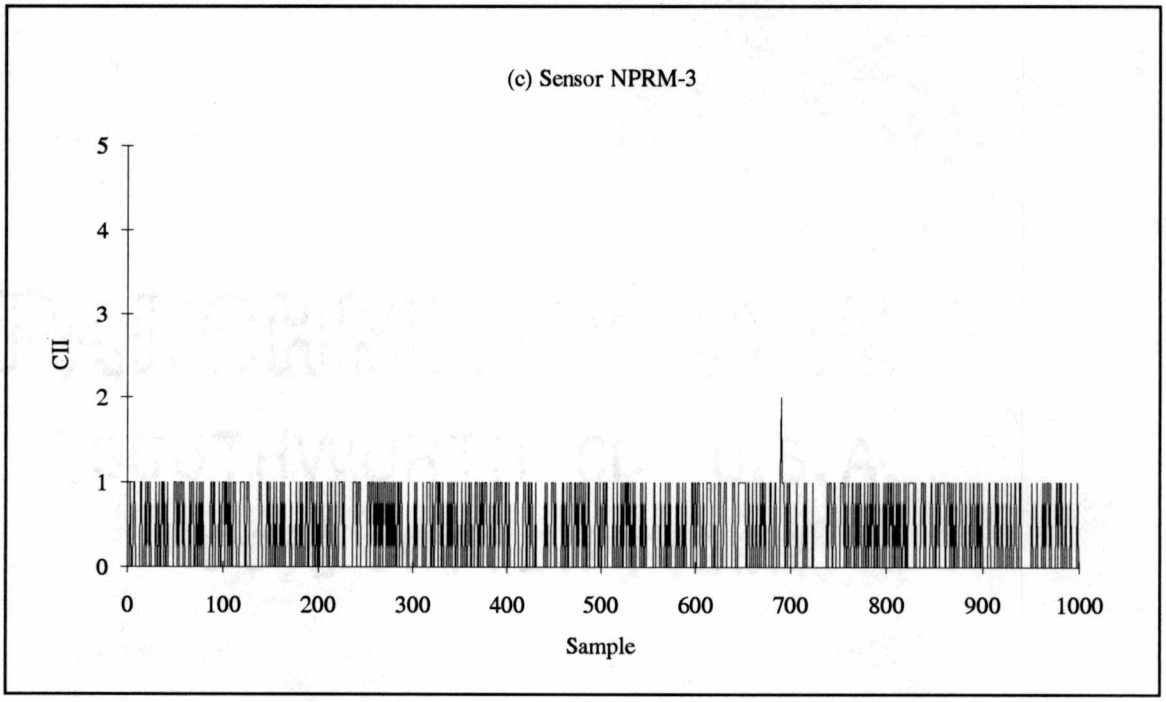


Figure 6.12 GCC Results of Nuclear Power Range Monitors for Case II.



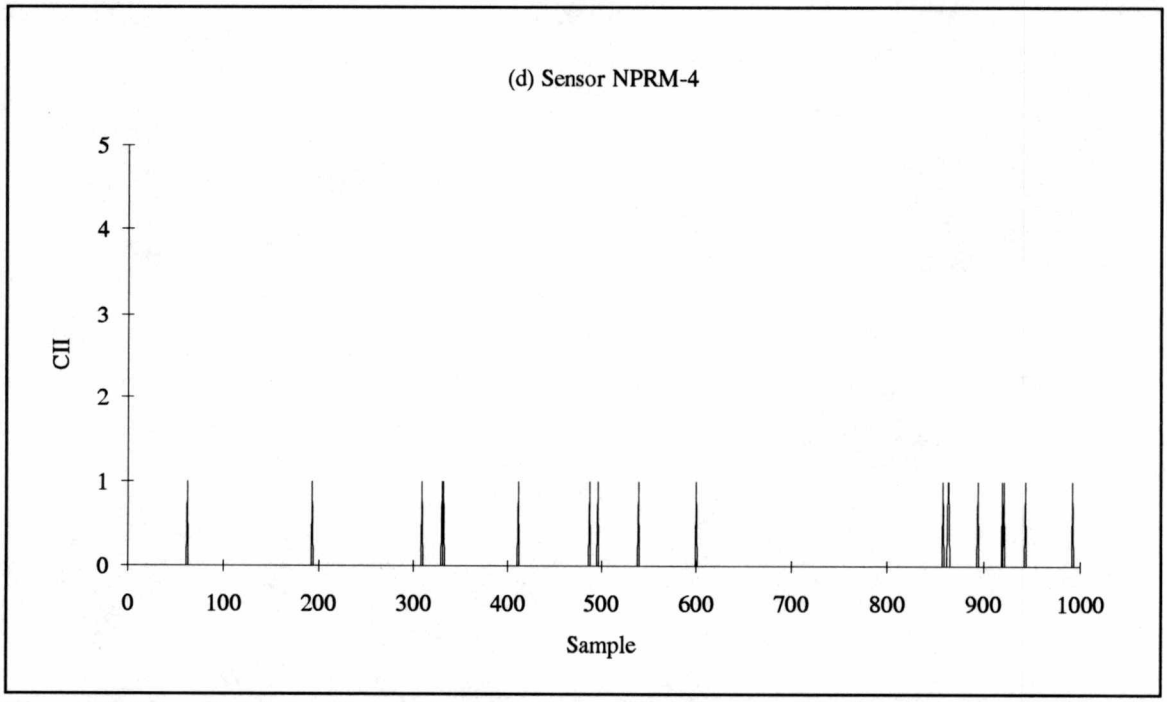


Figure 6.12 GCC Results of Nuclear Power Range Monitors for Case II (continued).

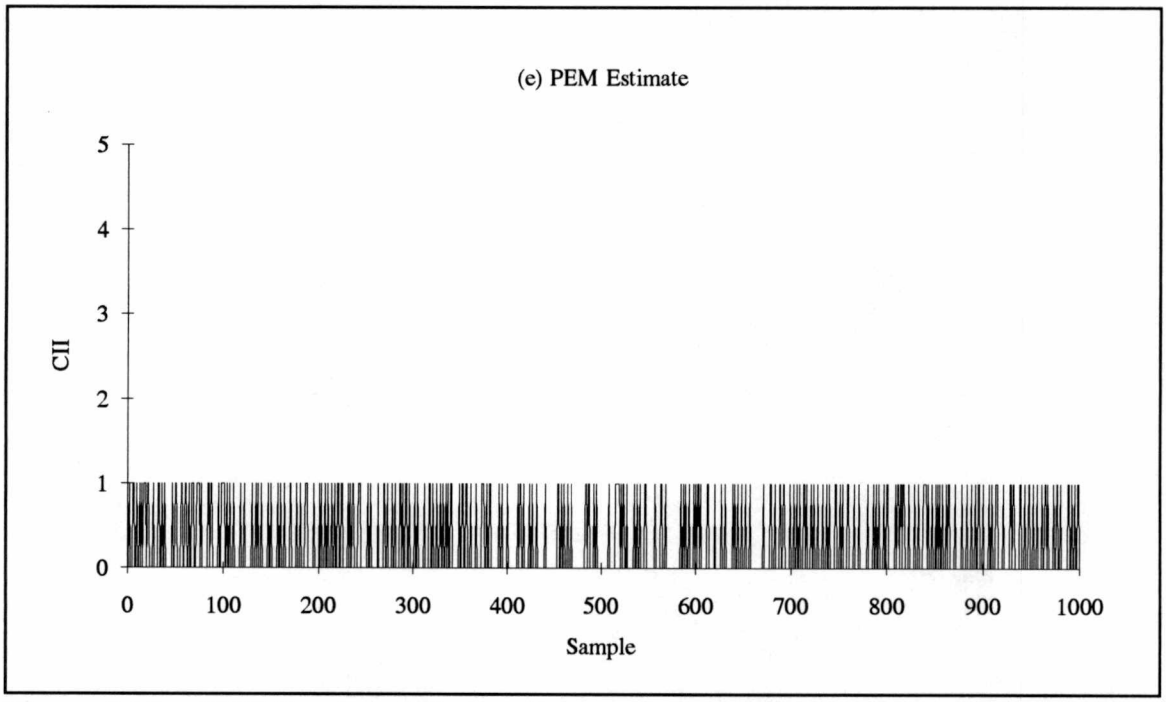


Figure 6.12 GCC Results of Nuclear Power Range Monitors for Case II (continued).

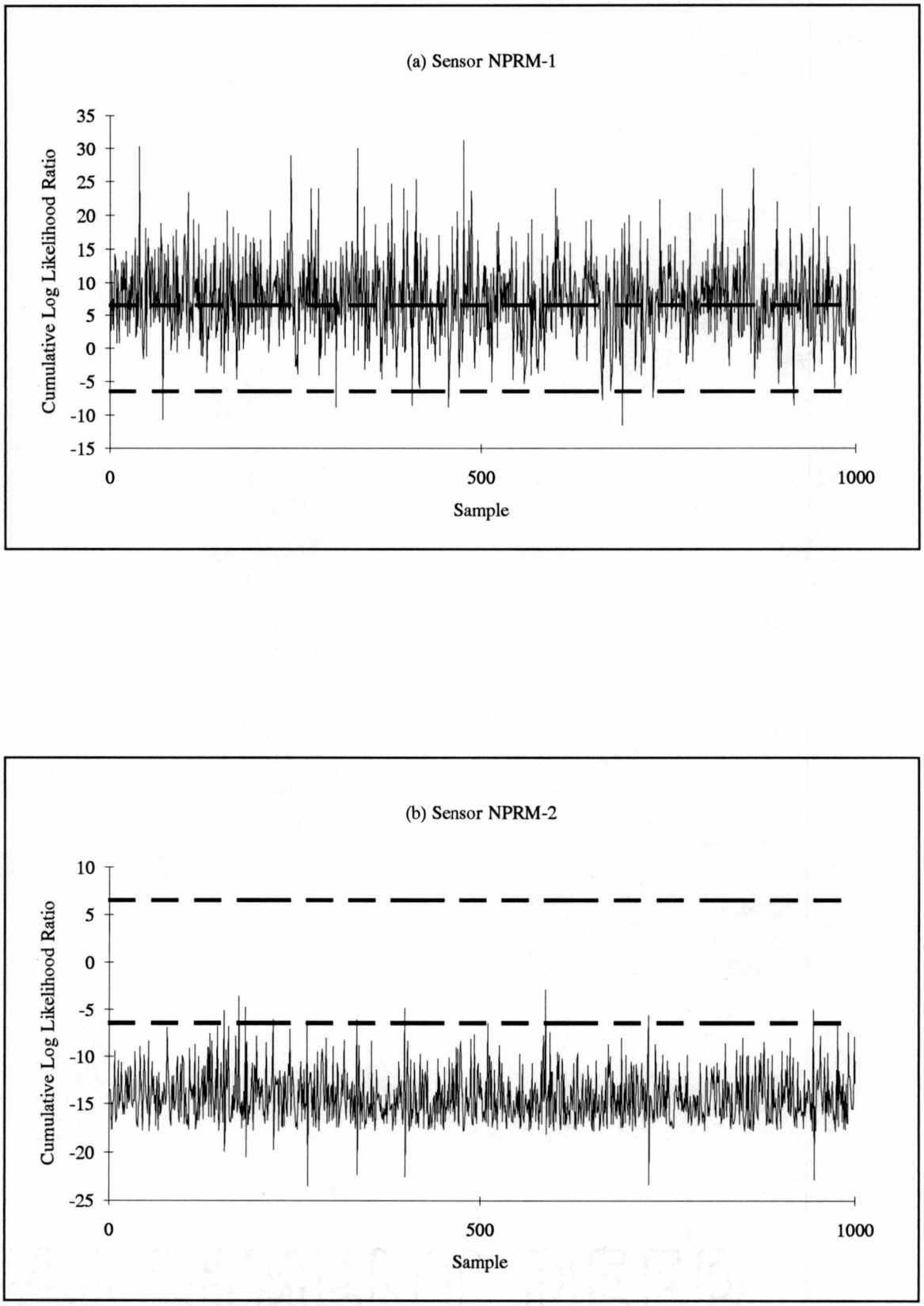
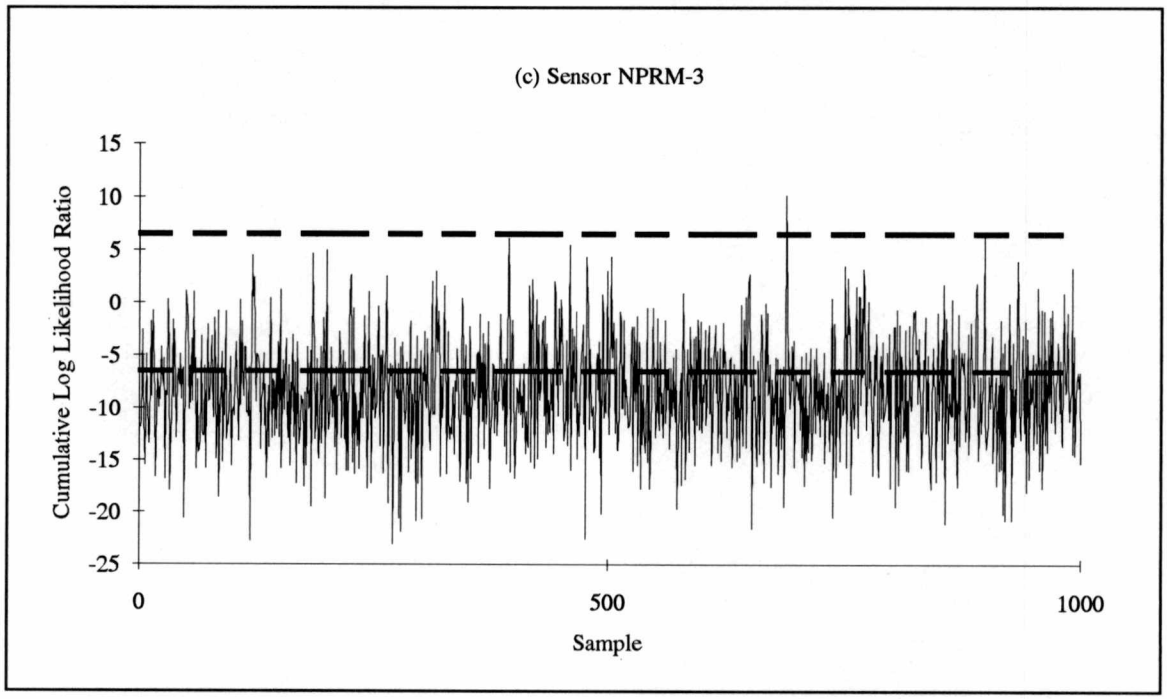


Figure 6.13 SPRT Results of Nuclear Power Range Monitors for Case II.



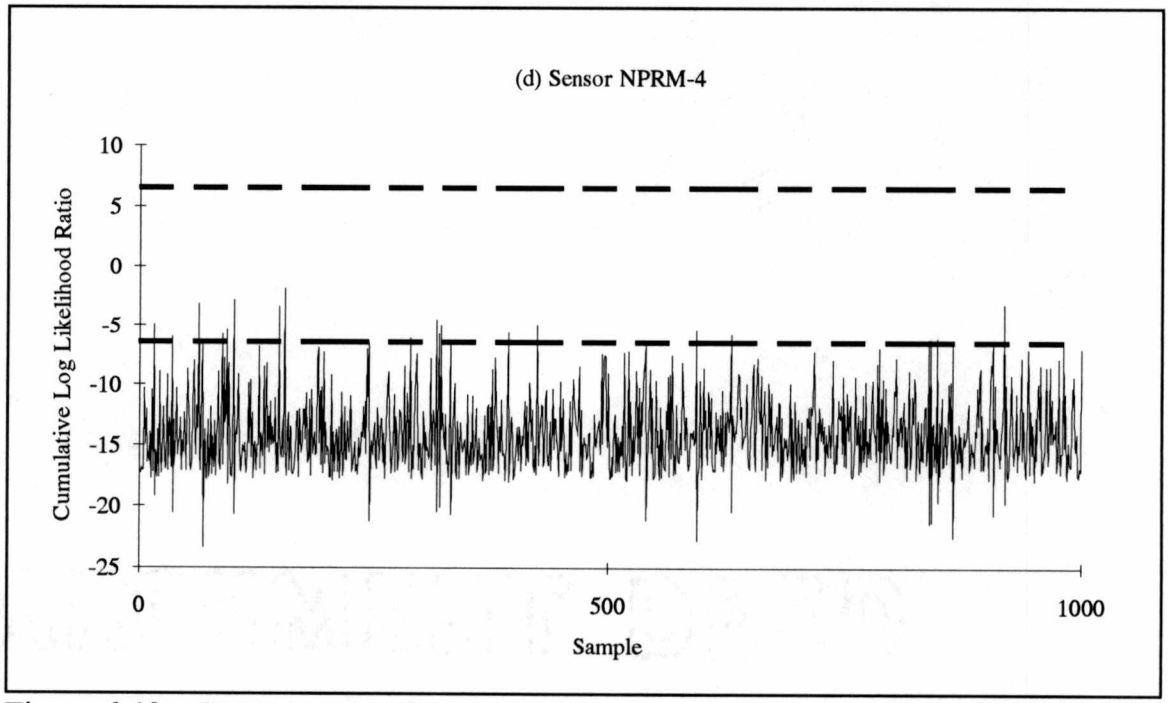


Figure 6.13 SPRT Results of Nuclear Power Range Monitors for Case II (continued).

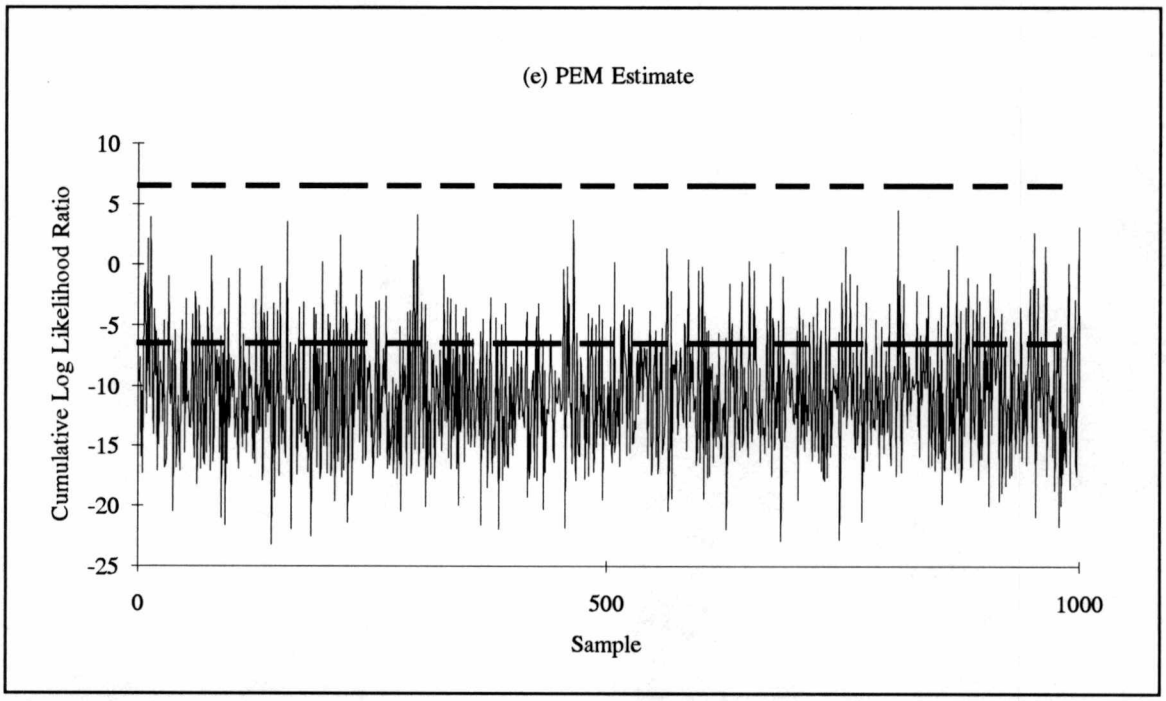


Figure 6.13 SPRT Results of Nuclear Power Range Monitors for Case II (continued).

(but not yet conclusive) indication of which sensor may be degrading. Since sensor NPRM-1 is ranked below all of the normal sensors with an SII index of 0.73 and a bias index of 0.22, it may be postulated that NPRM-1 is the degrading sensor.

The results of the SPRT provide a much more conclusive indication of the bias degradation of sensor NPRM-1. The MSTDN and MSTDD for NPRM-1 are given in Table 6.6 as 125 (index = 0.0) and 1.89 (index = 1.0) respectively. This is a clear indication of the bias degradation of NPRM-1 (with respect to the SPRT). All of the other sensors are well within the normal tolerance for the SPRT results. Thus for Case II, while the GCC results are indeterminate, the SPRT results appear very conclusive that NPRM-1 is drifting out of calibration.

Figures 6.12 through 6.13 show the time dependent behavior of the cumulative inconsistency indices and log likelihood ratios for all of the signals. In Figure 6.12(a), the small diamond located at the top of the spike near sample 500 indicates the sample that NPRM-1 was excluded from the GCC estimate (for 1000 samples, this corresponds to the 0.1% value for EXCL in Table 6.6). Figure 6.13(a) illustrates the SPRT decision that NPRM-1 is an abnormal sensor.

Case III - Single Sensor Error (2%)

The results of Case III are shown in Table 6.7 and Figures 6.14 through 6.16. This case illustrates the effect on the ICVS results of a single sensor (NPRM-1) with a two percent bias degradation. A two percent bias degradation represents a sensor which is outside of its allowable tolerance and is therefore clearly out of calibration. Table 6.7 shows that NPRM-1 has a sensor inconsistency index of 3.87 (SII index = 0.0) and a bias of 2.07% (bias index = 0.0). The value for the SII means that NPRM-1 was inconsistent with all of the redundant sensors for most of the samples (89.2% according to EXCL). All of the other sensors have very small values for the SII, and their bias values are nearly equal to the Case I (baseline) values. It is clear from the GCC results that NPRM-1 is the sensor that is out of calibration.

The results of the SPRT also provide a conclusive indication of the bias degradation of sensor NPRM-1. The MSTDN and MSTDD for NPRM-1 are given in Table 6.7 as infinity (index = 0.0) and 1.0 (index = 1.0) respectively. This is a clear indication of the bias degradation of NPRM-1 (with respect to the SPRT). All of the other sensors are approximately equal to their baseline SPRT results. Thus for Case III the SPRT results are very conclusive that NPRM-1 is drifting out of calibration.

Figures 6.15 through 6.16 show the time dependent behavior of the cumulative inconsistency indices and log likelihood ratios for all of the signals. In Figure 6.15(a),

Table 6.7 ICVS Summary for Case III.

CALIBRATION VERIFICATION SUMMARY

	SIGNAL 1	SIGNAL 2	SIGNAL 3	SIGNAL 4	SIGNAL 5
Signal Statistics					
MEAN	101.21	99.29	98.87	99.35	99.00
STD DEV	.22	.25	.25	.26	.25
SKEWNESS	-.11	-.01	.00	-.23	-.01
KURTOSIS	.93	.99	.99	1.02	.87
Generalized Consistency Checking Results					
% EXCL	89.20	.00	.00	.00	.00
SII	3.87	.06	.11	.04	.10
BIAS	2.07	.15	-.27	.21	-.14
SII INDEX	.00	1.00	.99	1.00	1.00
BIAS INDEX	.00	.98	.94	.96	.98
Sequential Probability Ratio Test Results					
MSTD NORM	-1.00	1.03	1.17	1.08	1.06
MSTD DEGR	1.00	-1.00	1000.00	-1.00	-1.00
NORM INDEX	.00	1.00	1.00	1.00	1.00
DEGR INDEX	1.00	.00	.00	.00	.00

ESTIMATE MEAN = 99.14

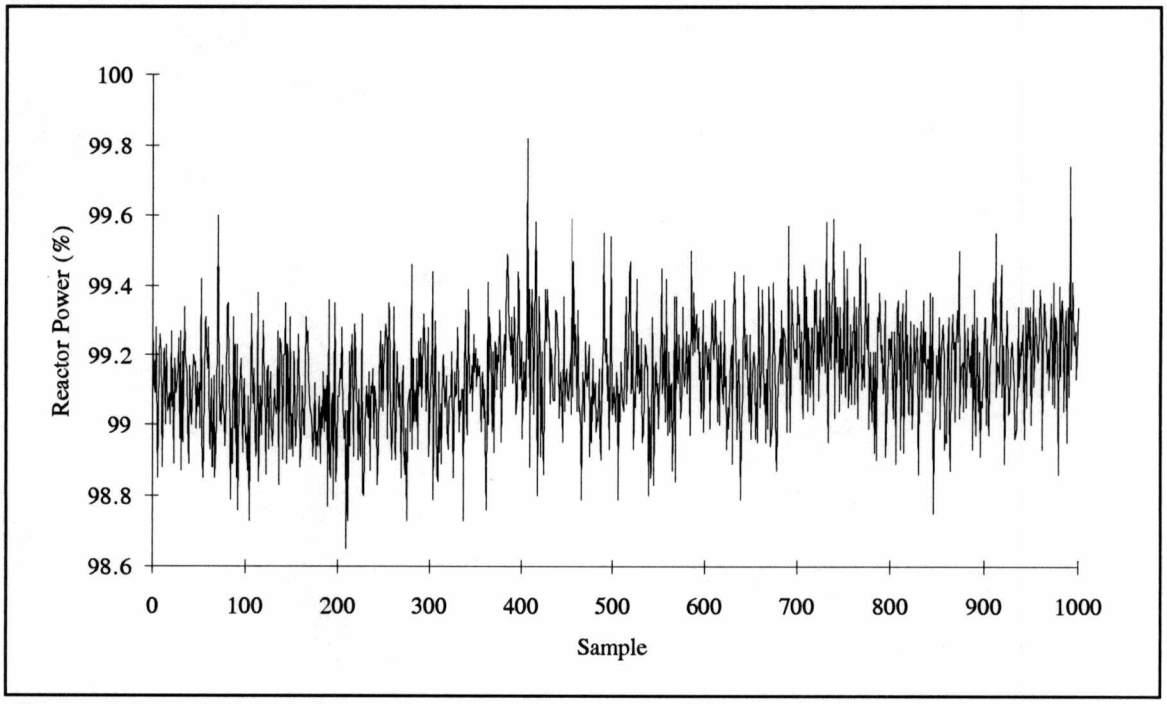
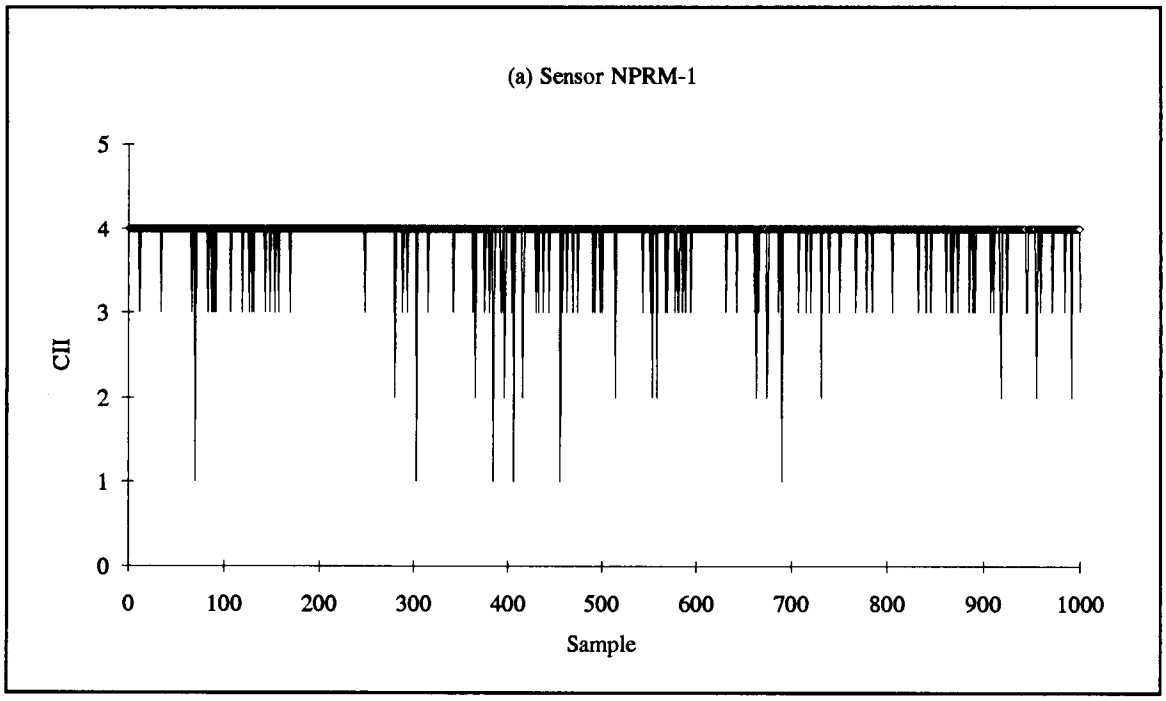


Figure 6.14 GCC Estimate for Case III.



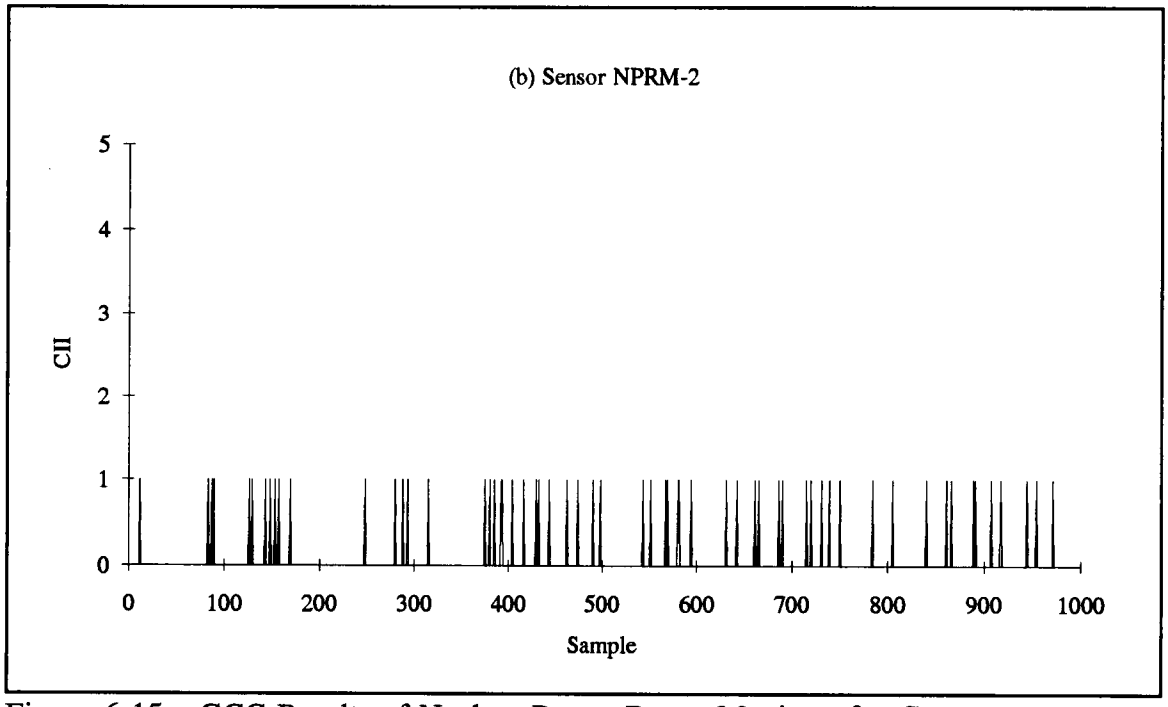
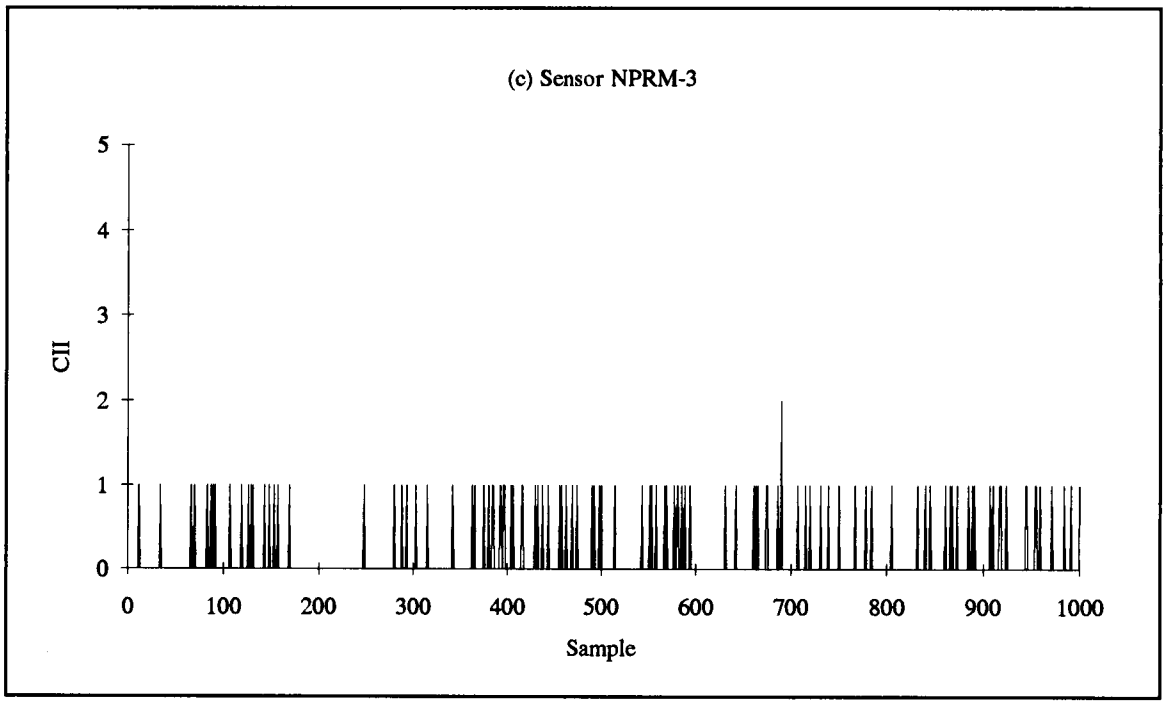


Figure 6.15 GCC Results of Nuclear Power Range Monitors for Case III.



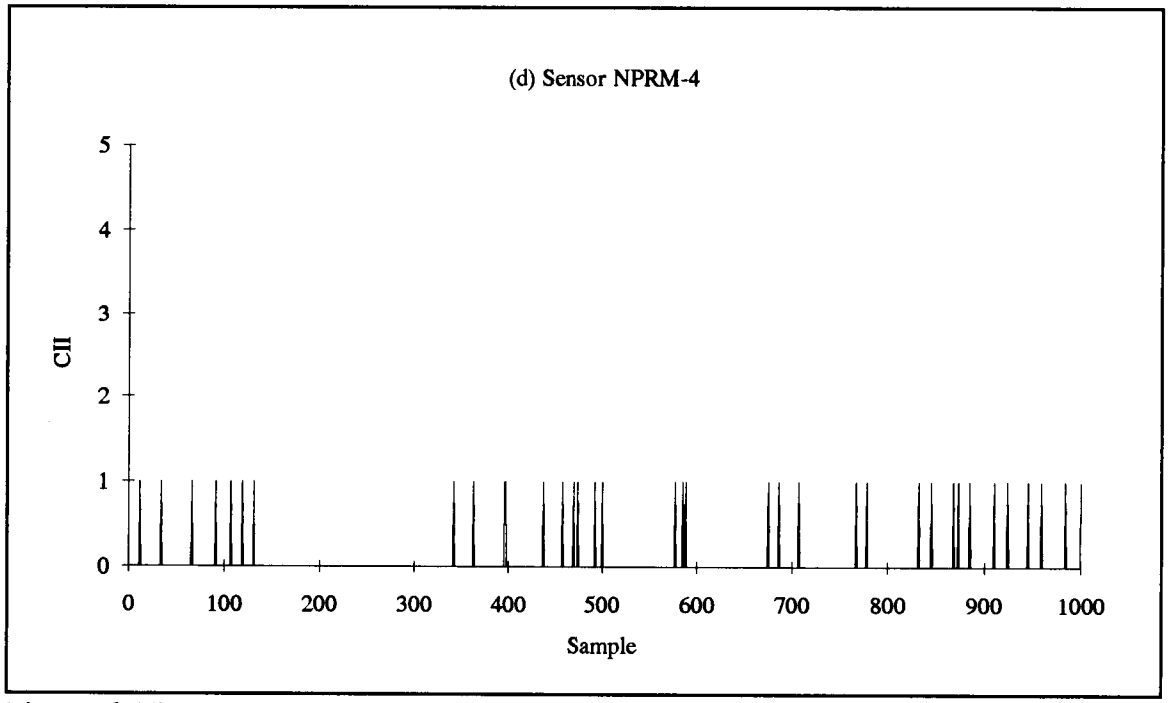


Figure 6.15 GCC Results of Nuclear Power Range Monitors for Case III (continued).

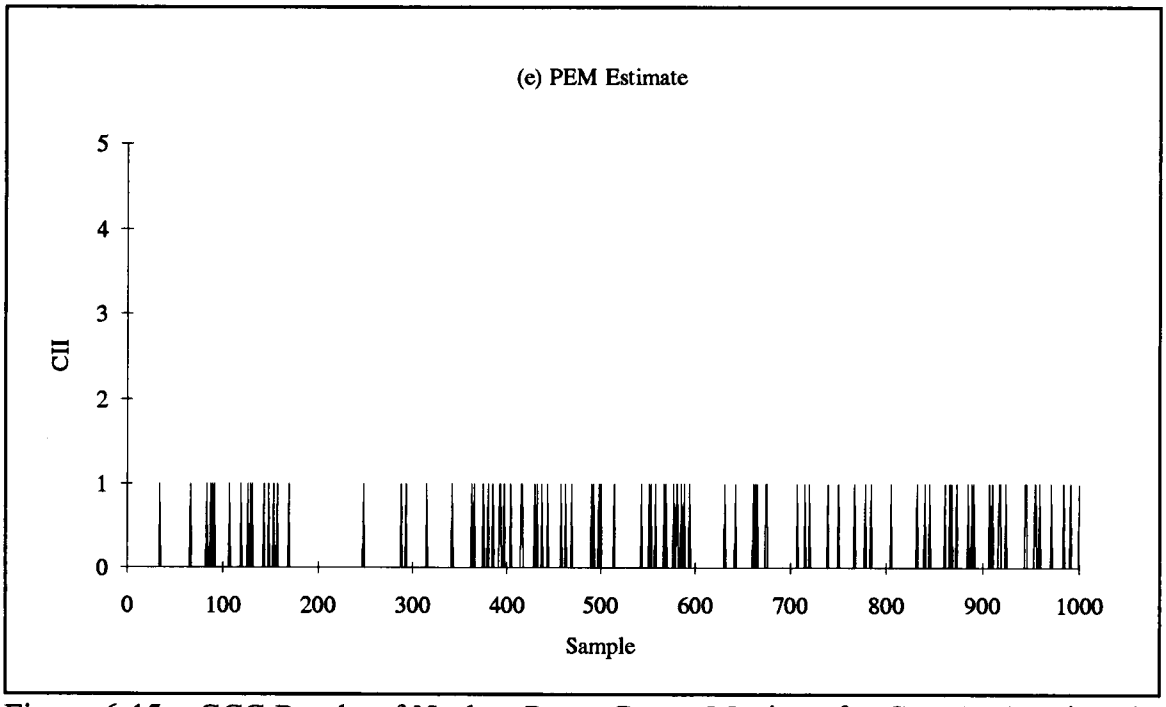
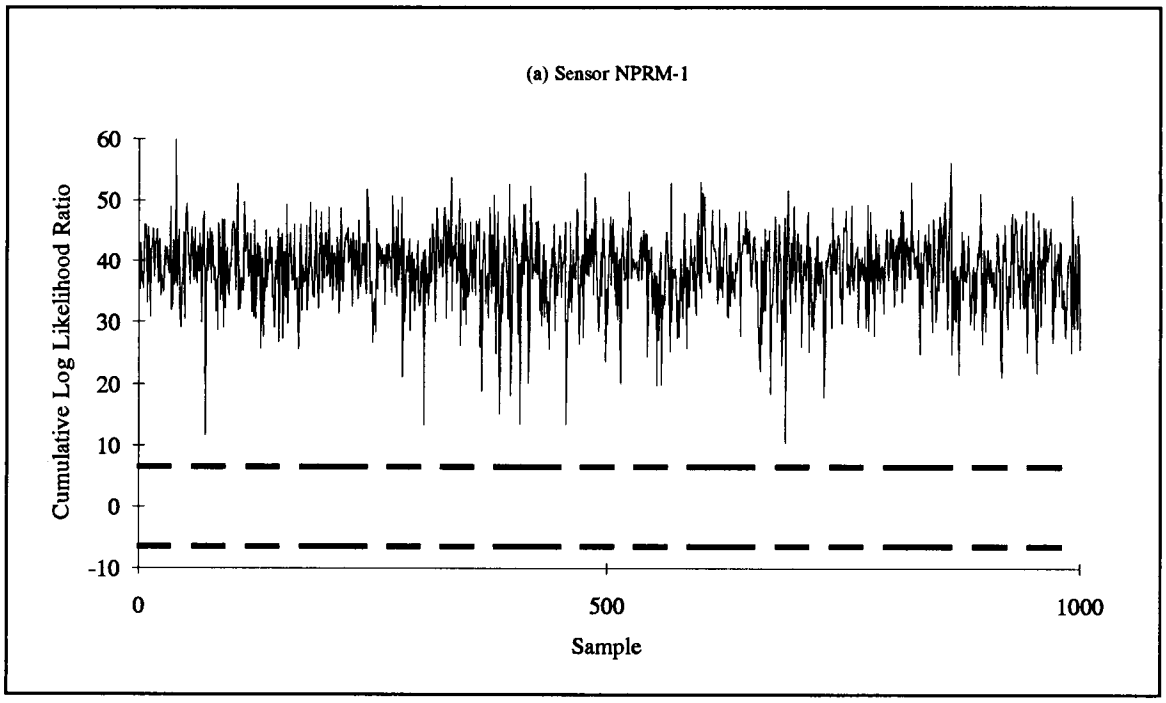


Figure 6.15 GCC Results of Nuclear Power Range Monitors for Case III (continued).



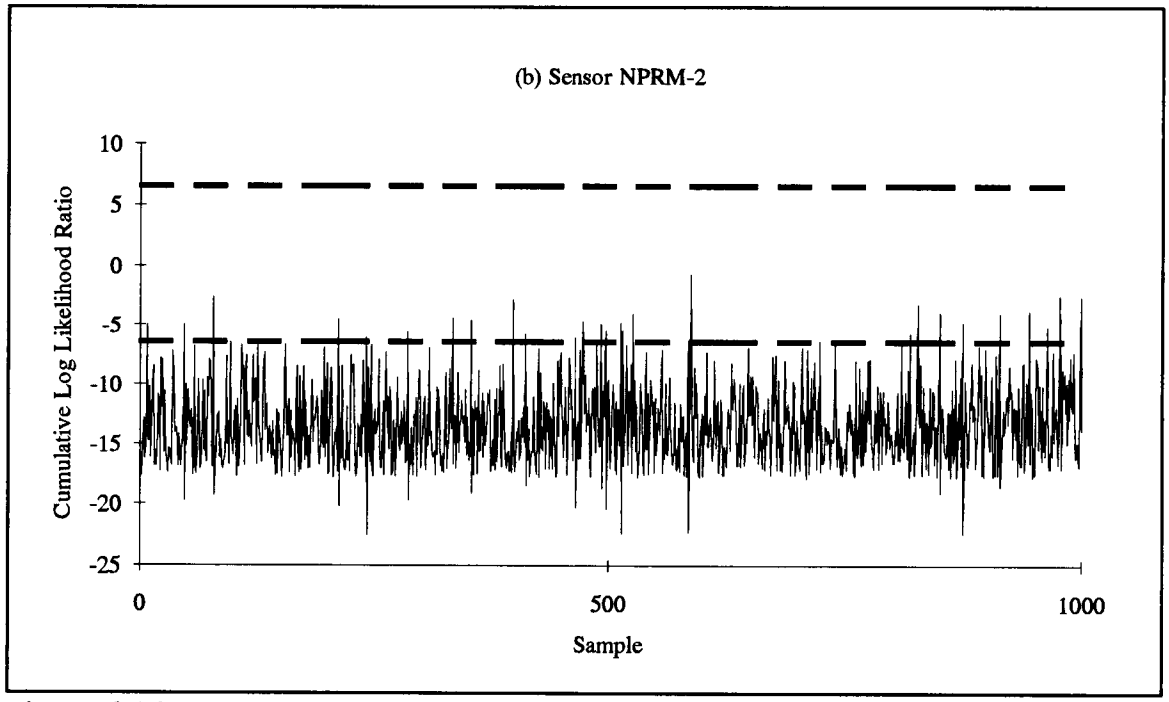
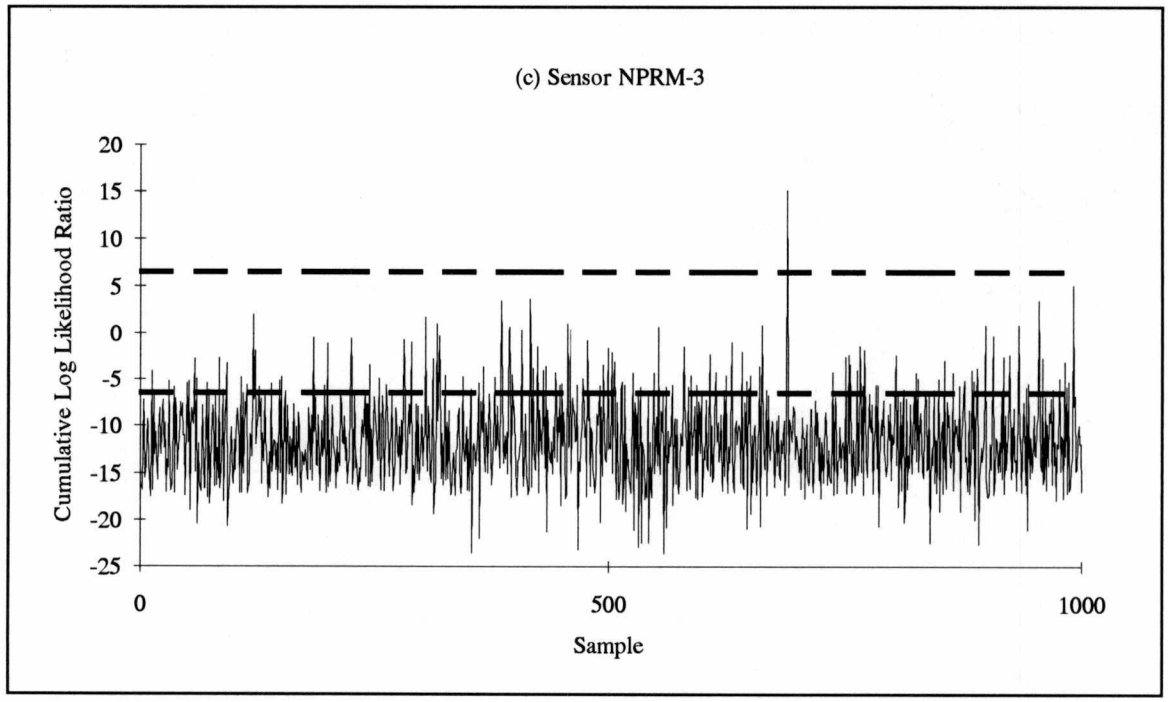


Figure 6.16 SPRT Results of Nuclear Power Range Monitors for Case III.



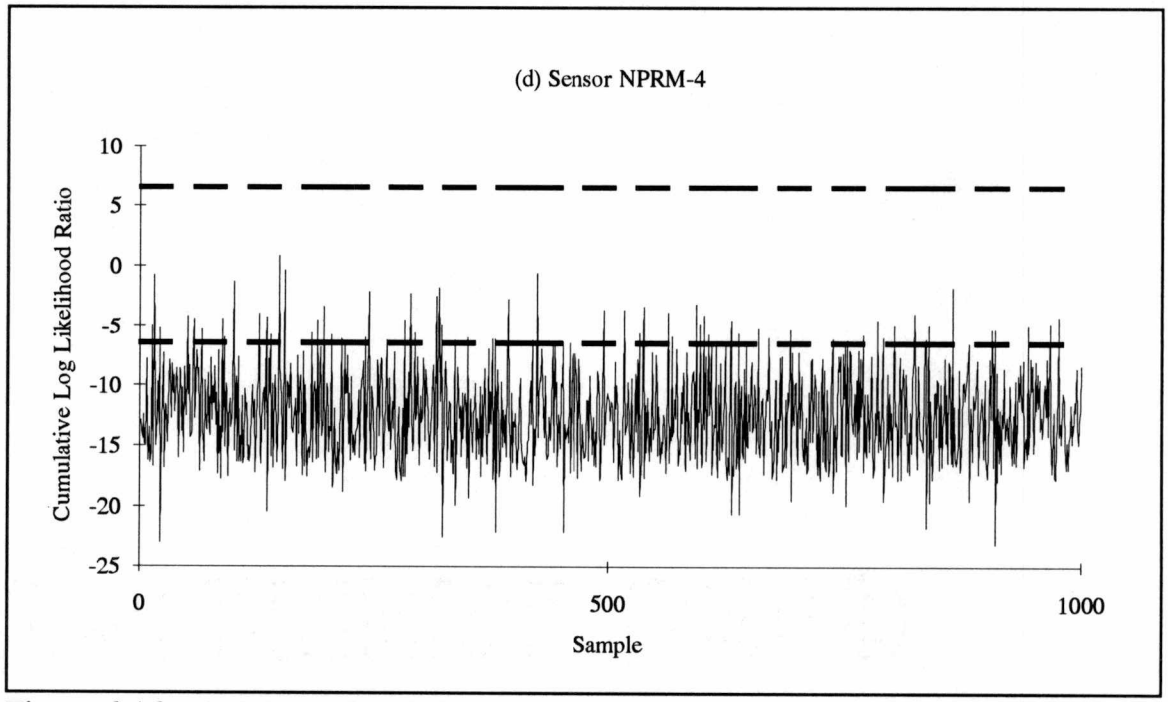


Figure 6.16 SPRT Results of Nuclear Power Range Monitors for Case III (continued).

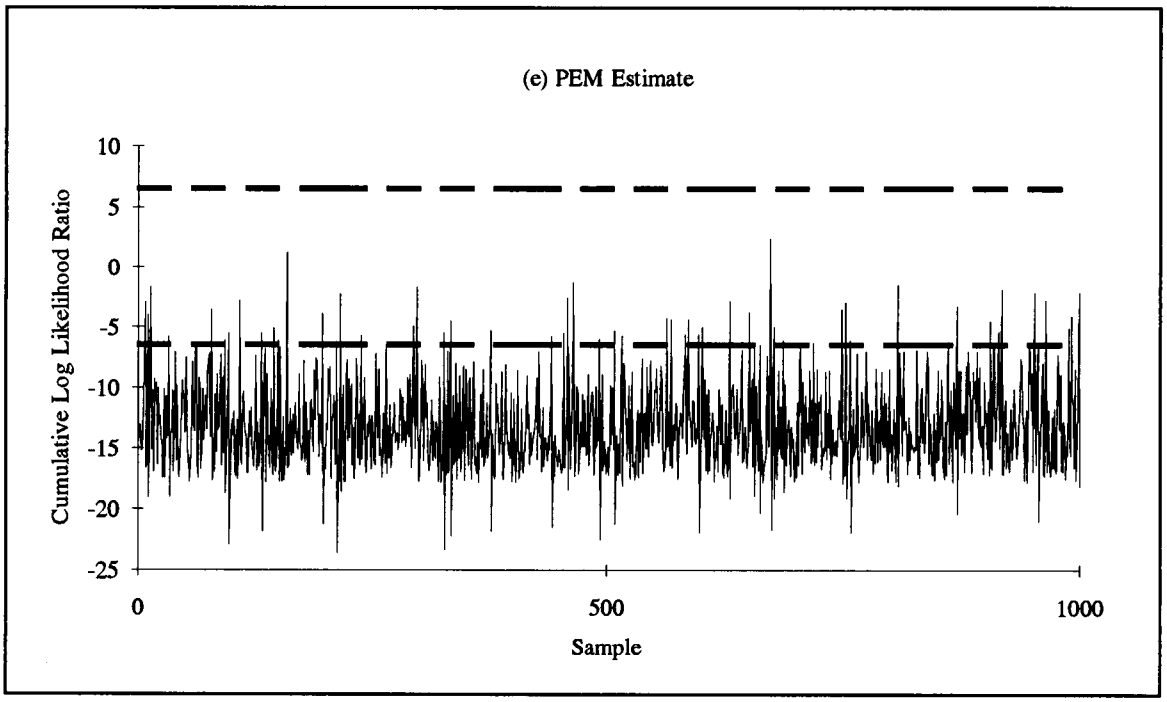
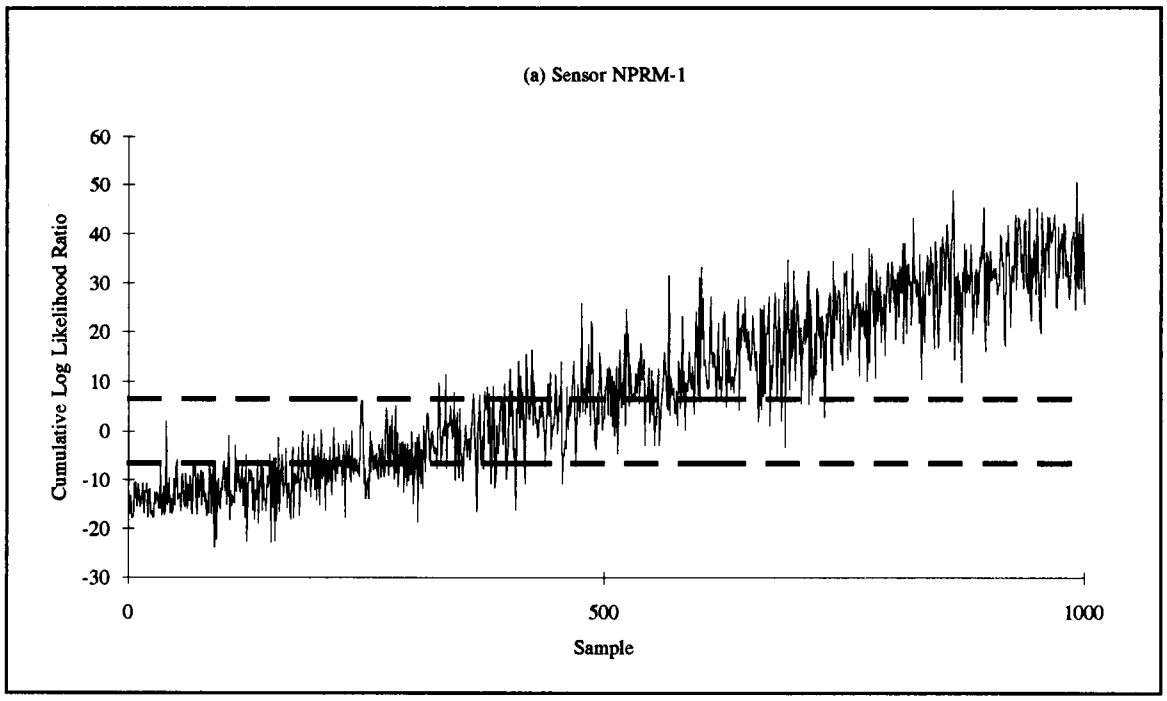


Figure 6.16 SPRT Results of Nuclear Power Range Monitors for Case III (continued).

the small diamonds located at the top of the spikes (this appears as a thick black line due to the density of plotted points) throughout the sample space indicate that NPRM-1 was excluded from the GCC estimate for the majority of the samples (this corresponds to the 89.2% value for EXCL in Table 6.7). Figure 6.16(a) illustrates the SPRT decision that NPRM-1 is an abnormal sensor. Note that the values for the log likelihood ratio are entirely above the degraded threshold.

Case IV - Single Sensor Error (Ramped from 0% to 2%)

The purpose of this case is to illustrate the response of the SPRT to a gradual bias drift. This illustrates the capability of the SPRT to trend a sensor's bias degradation. In practice this type of drift is not likely to be observed using batch sampling, but may be observed if the sensors are continuously monitored. Figure 6.17(a) shows the log likelihood ratio as the bias of sensor NPRM-1 is increased from nominal plus 0% to nominal plus 2%. In the region from approximately 300 to 500 samples (corresponding to 0.6% to 1.0% bias error) values of the log likelihood ratio are found between the normal and degraded bounds, and the SPRT results are indeterminate. The onset of this region roughly corresponds to one half of the specified SPRT faulted sensor bias (refer to Table 6.4), which is the critical cutoff y_c shown in Figure 4.3. This is the point at which the probability of normal vs. degraded membership is approximately equal. In this region, the log likelihood ratios for the other sensors remain at or below their normal bounds. Thus the SPRT is a good indicator for trending a single degrading sensor.



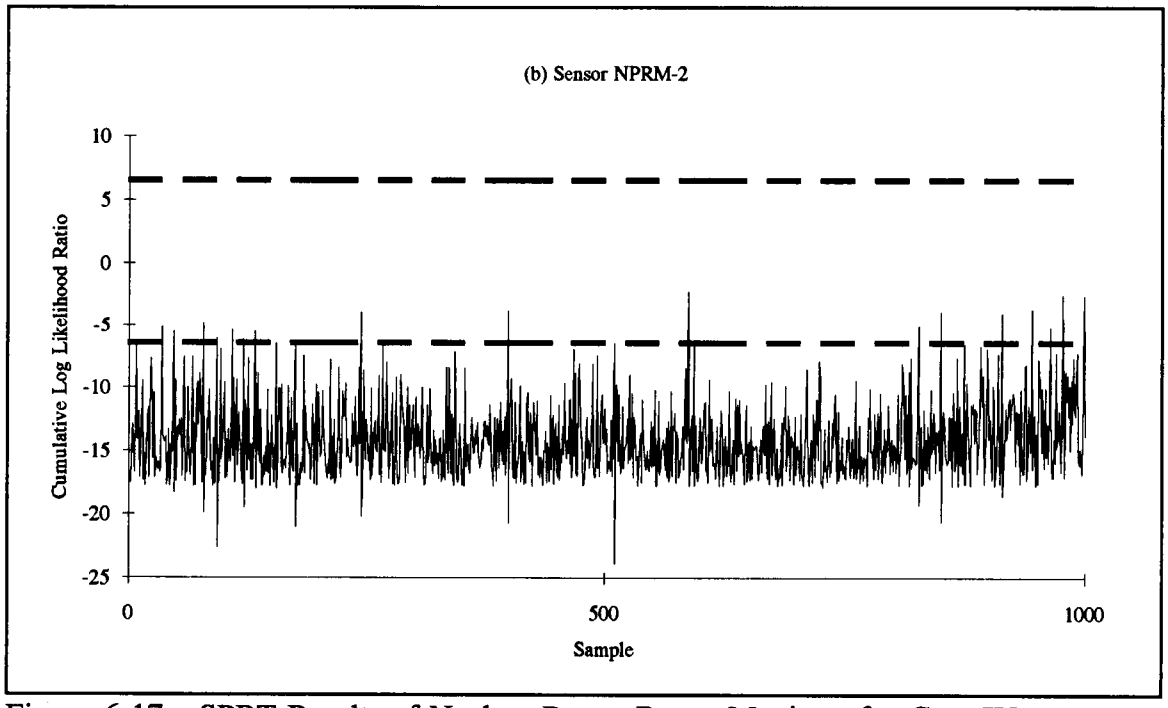
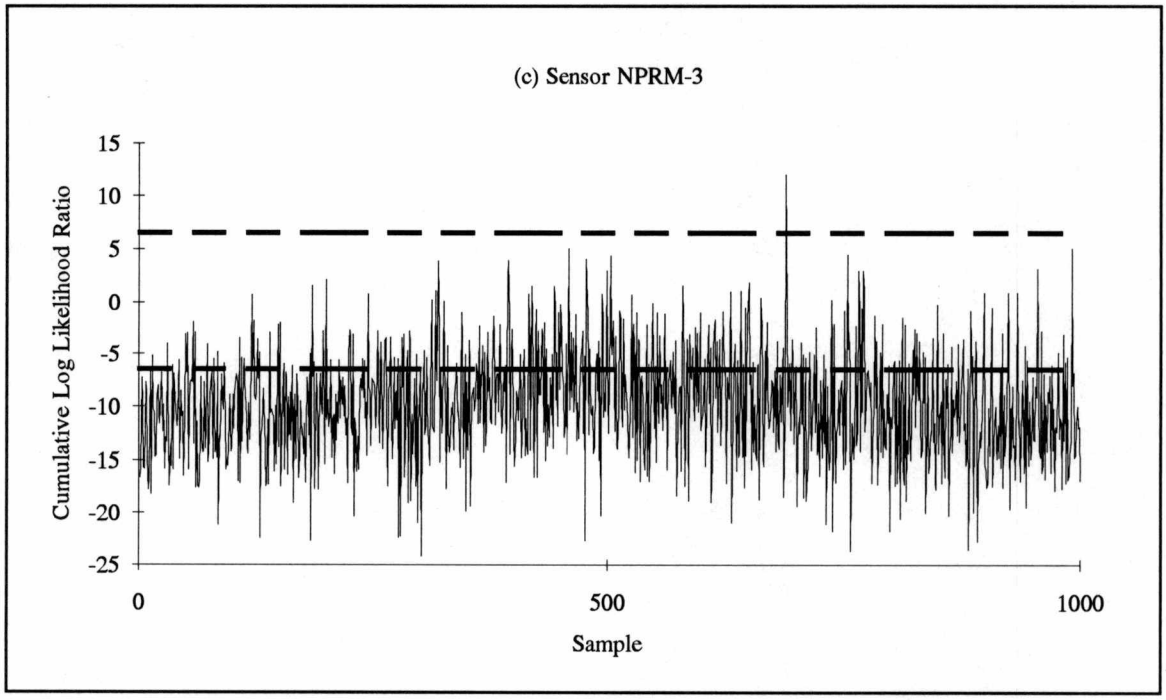


Figure 6.17 SPRT Results of Nuclear Power Range Monitors for Case IV.



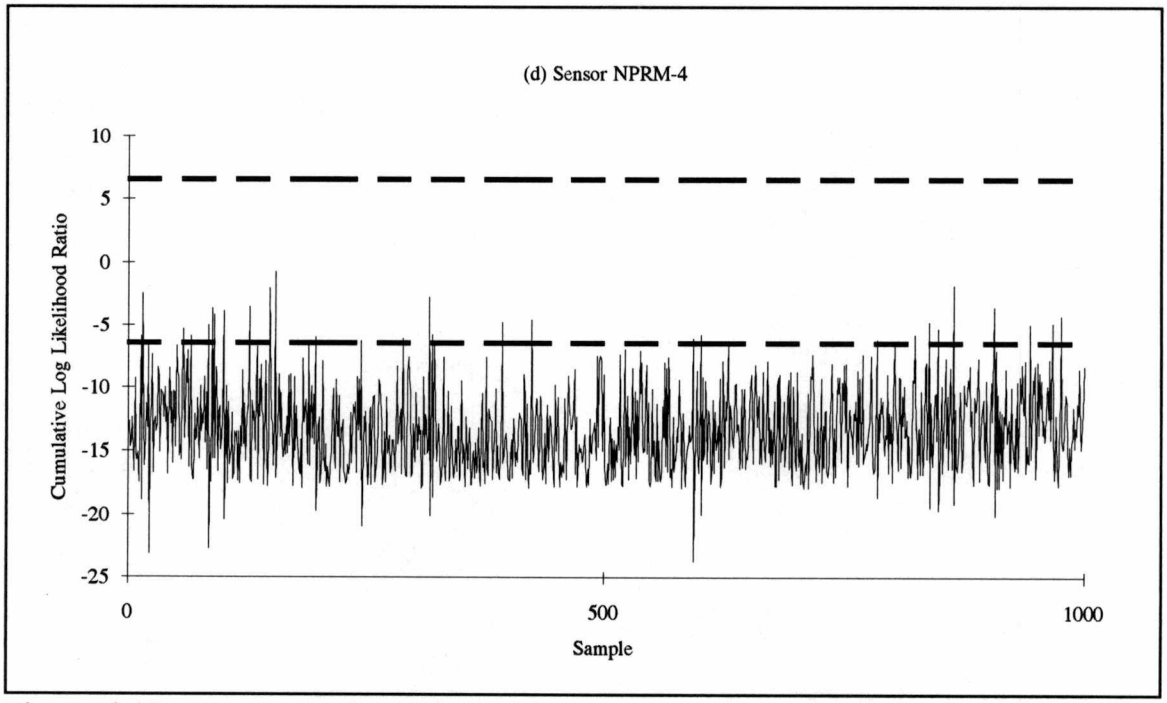


Figure 6.17 SPRT Results of Nuclear Power Range Monitors for Case IV (continued).

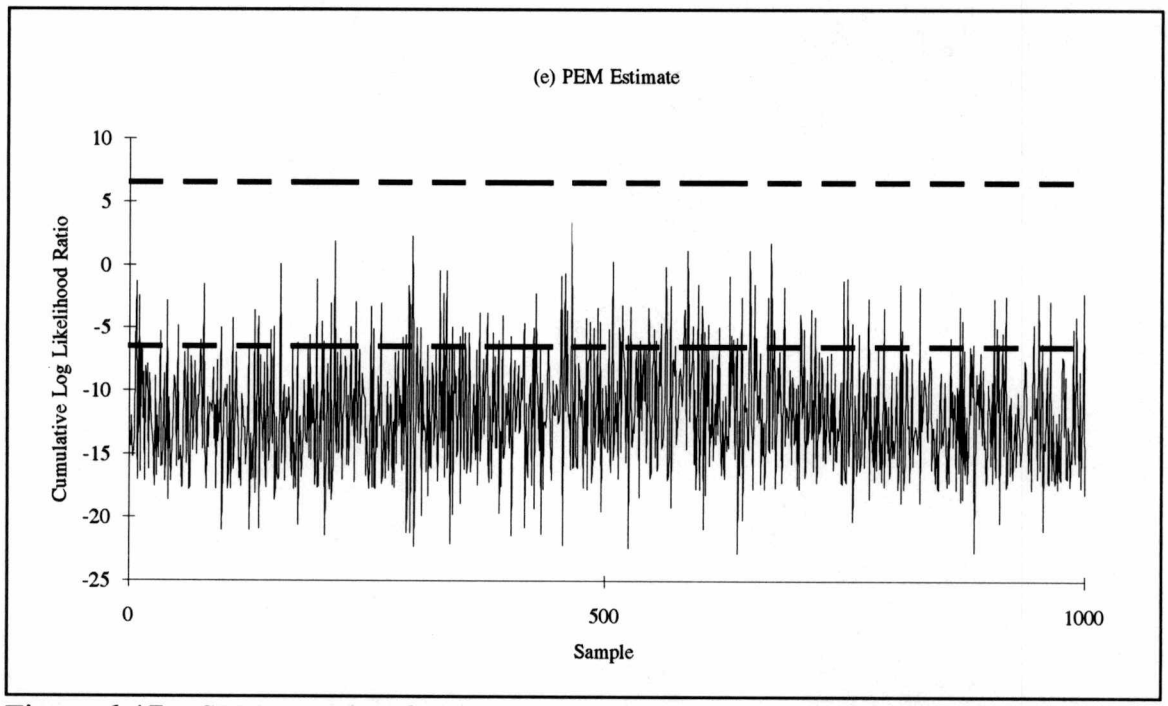


Figure 6.17 SPRT Results of Nuclear Power Range Monitors for Case IV (continued).

Case V - Two Sensor Error (+1%, +1%)

This case illustrates the effect on the ICVS results of two sensors (NPRM-1 and NPRM-2) that both have a bias degradation of +1%. Degradation of multiple sensors may occur randomly, but is more likely to be the result of a common cause failure. This includes personnel or equipment failures during the calibration procedure, manufacturer design or fabrication flaws, and installation or maintenance errors. A common cause bias degradation for two sensors of +1% was chosen to demonstrate a case for which the results of the ICVS are indeterminate.

The results of Case V are shown in Table 6.8. The results indicate the inability of the ICVS to conclusively identify the degraded sensors. The presence of two partially degraded sensors has biased the GCC estimate by 0.4% (to 99.54%) from the baseline case, thus changing the results for all of the sensors. Note that the SII and BIAS of sensors NPRM-1, NPRM-2, NPRM-3, and the PEM estimate are all of similar magnitude. The SPRT results also show similar results for sensors NPRM-1, NPRM-2, and NPRM-3. It is not clear from these results which sensors (or groups of sensors) have drifted.

To show the effect of a larger bias degradation, the two sensor case was analyzed using a +2% bias degradation. The results of this analysis are given in Table 6.9. For a +2% drift of both sensors, the ICVS clearly identifies the faulted sensors. The same

Table 6.8 ICVS Summary for Case V.

CALIBRATION VERIFICATION SUMMARY

	SIGNAL 1	SIGNAL 2	SIGNAL 3	SIGNAL 4	SIGNAL 5
Signal Statistics					
MEAN	100.21	100.29	98.87	99.35	99.00
STD DEV	.22	.25	.25	.26	.25
SKEWNESS	-.11	-.01	.00	-.23	-.01
KURTOSIS	.93	.99	.99	1.02	.87
Generalized Consistency Checking Results					
% EXCL	.40	.50	.00	.00	.00
SII	.69	.68	.75	.04	.55
BIAS	.67	.75	-.67	-.19	-.54
SII INDEX	.76	.77	.72	1.00	.85
BIAS INDEX	.49	.50	.61	.97	.74
Sequential Probability Ratio Test Results					
MSTD NORM	8.20	7.81	3.75	1.07	2.14
MSTD DEGR	7.52	8.77	13.89	-1.00	47.62
NORM INDEX	.87	.88	.98	1.00	1.00
DEGR INDEX	.89	.85	.58	.00	.00

ESTIMATE MEAN = 99.54

Table 6.9 ICVS Summary for Case V Using a +2% Bias for Sensors NPRM-1 and NPRM-2.

CALIBRATION VERIFICATION SUMMARY

	SIGNAL 1	SIGNAL 2	SIGNAL 3	SIGNAL 4	SIGNAL 5
Signal Statistics					
MEAN	101.21	101.29	98.87	99.35	99.00
STD DEV	.22	.25	.25	.26	.25
SKEWNESS	-.11	-.01	.00	-.23	-.01
KURTOSIS	.93	.99	.99	1.02	.87
Generalized Consistency Checking Results					
% EXCL	92.40	90.90	.00	.00	.00
SII	2.92	2.91	.17	.01	.15
BIAS	2.09	2.18	-.24	.24	-.12
SII INDEX	.00	.00	.99	1.00	.99
BIAS INDEX	.00	.00	.95	.95	.99
Sequential Probability Ratio Test Results					
MSTD NORM	-1.00	-1.00	1.15	1.08	1.06
MSTD DEGR	1.00	1.00	66.67	-1.00	333.33
NORM INDEX	.00	.00	1.00	1.00	1.00
DEGR INDEX	1.00	1.00	.00	.00	.00

ESTIMATE MEAN = 99.11

result could also be achieved by reducing the allowable tolerance for the sensors. However, reducing the sensor tolerance would impose undue restrictions on the acceptance criteria for the ICVS tests.

Case VI - Two Sensor Error (+1%,-1%)

Case VI illustrates the effect on the ICVS results of two sensors, NPRM-1 and NPRM-2, that have bias degradations of +1% and -1%, respectively. This is similar to Case V, except the bias drift for the two sensors is in opposite directions. The results of Case VI are shown in Table 6.10. Note that the value of the process variable estimate (99.07%) is only slightly biased from the baseline case. This occurs because the bias drift of the faulted sensors tend to cancel each other out (whereas in Case V, they re-enforced each other). Thus the results for the normal sensors are expected to be close to their baseline values. The values of the SII and the BIAS for NPRM-1 and NPRM-2 clearly indicate that these sensors have degraded, while the values for NPRM-3, NPRM-4, and the PEM estimate are clearly normal. The results for the SPRT also demonstrate that NPRM-1 and NPRM-2 have degraded while the other sensors are normal.

Table 6.10 ICVS Summary for Case VI.

CALIBRATION VERIFICATION SUMMARY

	SIGNAL 1	SIGNAL 2	SIGNAL 3	SIGNAL 4	SIGNAL 5
Signal Statistics					
MEAN	100.21	98.29	98.87	99.35	99.00
STD DEV	.22	.25	.25	.26	.25
SKEWNESS	-.11	-.01	.00	-.23	-.01
KURTOSIS	.93	.99	.99	1.02	.87
Generalized Consistency Checking Results					
% EXCL	2.10	.10	.00	.00	.00
SII	1.64	.99	.37	.07	.26
BIAS	1.13	-.78	-.20	.28	-.08
SII INDEX	.07	.51	.93	1.00	.96
BIAS INDEX	.04	.46	.96	.94	.99
Sequential Probability Ratio Test Results					
MSTD NORM	-1.00	9.52	1.08	1.18	1.02
MSTD DEGR	1.18	5.68	-1.00	1000.00	-1.00
NORM INDEX	.00	.81	1.00	1.00	1.00
DEGR INDEX	1.00	.94	.00	.00	.00

ESTIMATE MEAN = 99.07

Case VII - Common Cause Failure (All Sensors)

This case shows the effect of a bias degradation of all redundant sensors resulting from a common cause failure. The intent of this case is to show an example in which the PEM estimate is inconsistent with all (or most) of the redundant sensors. Table 6.11 shows the ICVS results for this example. All of the results indicate that the four redundant sensors are completely consistent with each other, and inconsistent with the PEM estimate. With the information presented here, it is not possible to determine if the PEM estimate is in error or if the sensors have experienced a common cause degradation. The results of the ICVS tests are therefore indeterminate for this example, and further examination of the involved sensors is recommended. As a next step, the instrument technician may apply the ICVS to the inputs of the PEM estimate to determine if one of the input sensors is degraded.

The results of these test cases show that the ICVS can detect the bias drift of a single sensor before it is out of calibration. Identifying a two sensor bias drift is more difficult for a small change from the baseline, and requires a more severe bias drift. Case VII (all sensors drift) demonstrates that the ICVS can flag a potential common cause calibration failure. In all cases, it appears that the SPRT indicates a bias drift earlier than the GCC algorithm, and is thus a more sensitive measure of sensor bias drift.

Table 6.11 ICVS Summary for Case VII.

CALIBRATION VERIFICATION SUMMARY

	SIGNAL 1	SIGNAL 2	SIGNAL 3	SIGNAL 4	SIGNAL 5
Signal Statistics					
MEAN	100.21	100.29	99.87	100.35	99.00
STD DEV	.22	.25	.25	.26	.25
SKEWNESS	-.11	-.01	.00	-.23	-.01
KURTOSIS	.93	.99	.99	1.02	.87
Generalized Consistency Checking Results					
% EXCL	.00	.00	.00	.00	1.60
SII	.26	.26	.01	.29	.89
BIAS	.21	.30	-.12	.36	-1.00
SII INDEX	.96	.97	1.00	.96	.60
BIAS INDEX	.95	.92	.99	.90	.23
Sequential Probability Ratio Test Results					
MSTD NORM	1.12	1.18	1.04	1.27	58.82
MSTD DEGR	-1.00	1000.00	-1.00	-1.00	2.20
NORM INDEX	1.00	1.00	1.00	1.00	.00
DEGR INDEX	.00	.00	.00	.00	1.00

ESTIMATE MEAN = 99.99

7. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

7.1 Summary and Conclusions

The ICVS extends the technique of determining the calibration state of a set of redundant instruments beyond the method practiced in the nuclear industry today. Current methodology incorporates signal statistics into cross-checking of redundant sensors with a weighted average. Weighted averages are calculated based on individual instrument loop accuracies. The ICVS uses a consistency checking algorithm which provides sensor weights based on the level of inconsistency for each sample, and can exclude a sensor from the estimate that exceeds the prescribed tolerance of a sensor. Fuzzy membership functions are also used to provide a higher weight for sensors with a low inconsistency index, and a lower weight for sensors with a high inconsistency index. The consistency checking algorithm also provides an empirical estimate based on other plant process variables. This estimate adds a functionally diverse point of redundancy that is useful in detecting common mode failures. Finally, the ICVS uses a Sequential Probability Ratio Test (SPRT) as an additional means of determining the calibration state of a sensor. The SPRT is an efficient log likelihood ratio test that can compare sensor measurements against normal and degraded distributions, and decides if the measurements are from the normal or degraded distributions. The SPRT is a useful test to trend historical changes in a sensor's behavior.

The results of analyses performed on the artificial data and on the PWR data indicate that the performance characteristics for the ICVS provide a sensitive measurement of the calibration state of a sensor. The base case (Case I) provides a good estimate of the normal behavior of a group of redundant sensors, including the normal bias of each sensor. A single sensor that experiences a bias drift can be identified as a potential problem even before the sensor tolerance is exceeded (as in Case II). If the drift becomes excessive, it is clearly singled out and excluded from the process variable estimation. In the case of multiple sensor failures (double failures as examined in Cases V and VI), there is a wider region of ambiguity. While the sensor bias drifts are still small, the sensors are still within tolerance and are not identified as degrading. The bias drift must become significant before the ICVS can determine which sensors are drifting. For the common mode failure (Case VII), the inconsistency of the redundant sensors with the empirical estimate clearly flags a potential problem. However it is not possible to identify if it is a true common mode failure or an inaccuracy in the empirical estimate. It should be noted that for all of the above cases, when the performance characteristics deviate from their baseline values, or become indeterminate, the main result of the ICVS tests is that the calibration state of a sensor *cannot be verified*, thus requiring a response from plant personnel.

In conclusion, the goal of any calibration verification methodology is to confirm that a sensor is within calibration tolerance. If the results of such a methodology are indeterminate or indicate a failure, then the calibration state of the sensor in question

cannot be verified, and the sensor is scheduled for re-calibration. Thus the emphasis on such a system is on detecting the *success*, rather than the *failure*, of a sensor. The ICVS meets this criterion.

7.2 Recommendations for Future Work

There are numerous improvements and expansions that could be made to a methodology such as this. A few of them are listed that are within the scope of the existing system which may improve the ability of the ICVS to perform its function.

1. Add the capability for on-line monitoring. The system currently operates as a batch system. On-line monitoring would allow low priority alarms to alert instrument technicians to incipient failures. Computer resources can be minimized by only retaining the ICVS summary data in a data base over a longer period.

2. Incorporate other probability distributions for use in error analysis and in the SPRT. Gaussian distributions are currently used in the SPRT, and for determining "normal" allowable tolerance. While most steady-state measurements approximate a Gaussian distribution, asymmetries or hysteresis effects in a sensor may produce other distributions.

3. Develop empirical models over a larger range of operating conditions. The models should have some overlap in their domains, and should be centered around useful regions. For example, the ICVS may be applied at plateaus during power ascension where surveillance tests may be expected.

4. Incorporate the GCC estimation algorithm into the inputs of the empirical model. The empirical model currently uses one sensor from each input variable. By using the GCC algorithm to generate an estimate for each input variable, the empirical estimate would be more resistant to single failures of input sensors. A similar technique, called Multivariate Generalized Consistency Checking, has been applied in the Signal Validation System [2] developed at the University of Tennessee.

5. Perform a rigorous test program using steady-state power plant data. Our available data were limited in size and quality. The algorithm should be tested under various conditions and with a larger set of process variables. Also, the sampling frequency should be increased to obtain a better defined distribution.

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REFERENCES

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APPENDICES

APPENDIX A - Description of Software

The Instrument Calibration Verification System (ICVS) software was written in Microsoft FORTRAN version 5.1 for use in the Windows operating environment. Any IBM compatible personnel computer (PC) that can operate Microsoft Windows version 3.1 can also run the ICVS program. As the program is executed, the output is directed in tabular form to a set of "child" windows. The data inside the child windows may be imported to a spreadsheet, database, word processor, text editor, or any other Windows program that supports the Windows clipboard (see the Windows manual for detailed information). In this thesis, I exported the ICVS output to a Microsoft Excel for Windows spreadsheet for the creation of graphs.

Input Data File Structure

The input data files contain the sensor data to be analyzed. The ICVS uses two input data files; 1) the *measurement file* which contains the sensor measurements (file extension ".DAT"), and 2) the *sample file* which contains information about the measurement file (file extension ".SAM"). Both files use the same file name combined with the above noted file extensions. The first three records of the sample file contain the number of channels, the number of measurements (samples), and the sampling interval (in seconds) of the measurement file. The data type for these numbers is REAL, and the record length is four bytes. The subsequent records in the

sample file contain the labels for each of the sensors, and must be equal to the number of channels (i.e., every channel has a label). These are defined as the CHARACTER data type, and have a record length of 20 bytes. (NOTE: To read the first three records, the sample file must be opened as DIRECT ACCESS with a record length equal to four bytes. To read the channel labels, the sample file must then be closed, and re-opened as DIRECT ACCESS with a record length of 20 bytes. The channel labels will start with the second record.) The measurement file is arranged sequentially by sample, then by channel. Thus the first record corresponds to the first sample of the first channel, the second record is the first sample of the second channel, and so forth. If there are N channels, the first N records correspond to the first sample for all N channels, respectively. Record number N+1 starts the cycle again for the second sample. Thus for M samples, there will be a total of NxM records in a measurement file. The data type for measurement file is REAL, and the record length is four bytes.

Executing the ICVS Program

When the ICVS program is executed, the window shown in Figure A.1 appears. The selections are 1) Input Channel Information, 2) Execute Main Program, and 3) Exit Program. Selection 1) must be chosen first to provide the input data about the measurement data files, channels to be analyzed, and the analysis tolerances. Figure A.2 illustrates the parameters that are required in the Input Menu. The first

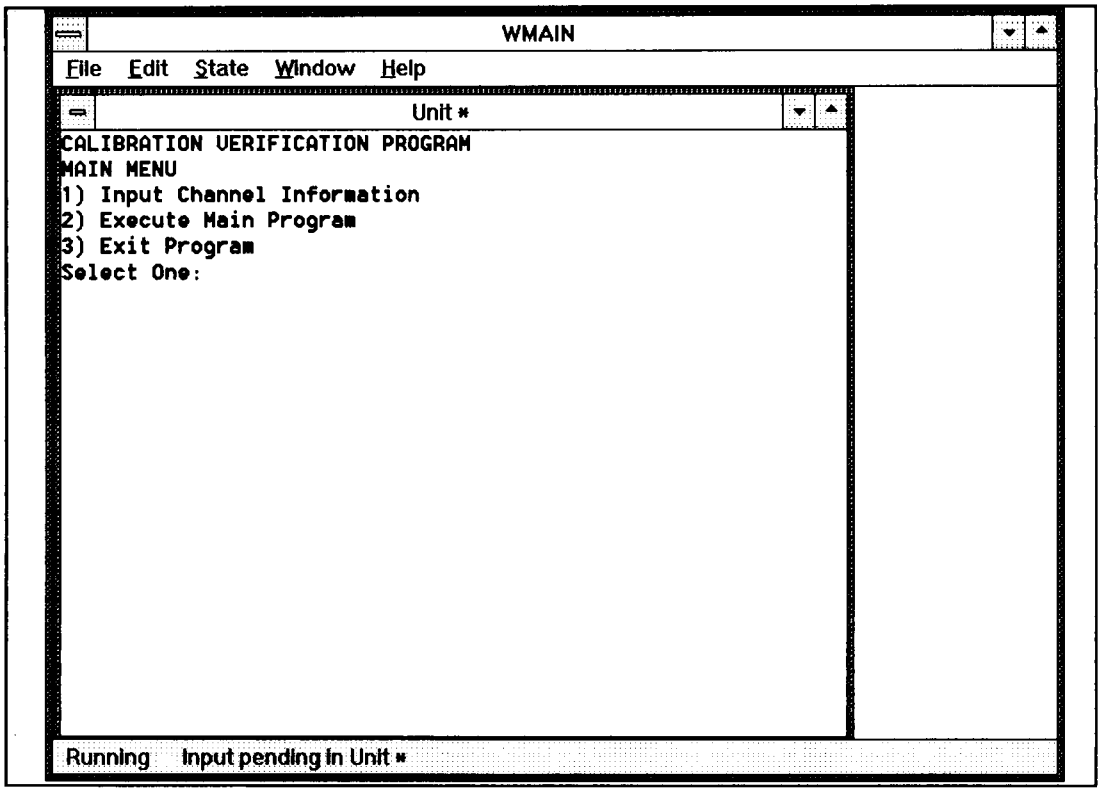


Figure A.1 Initial Input Window for the ICVS.

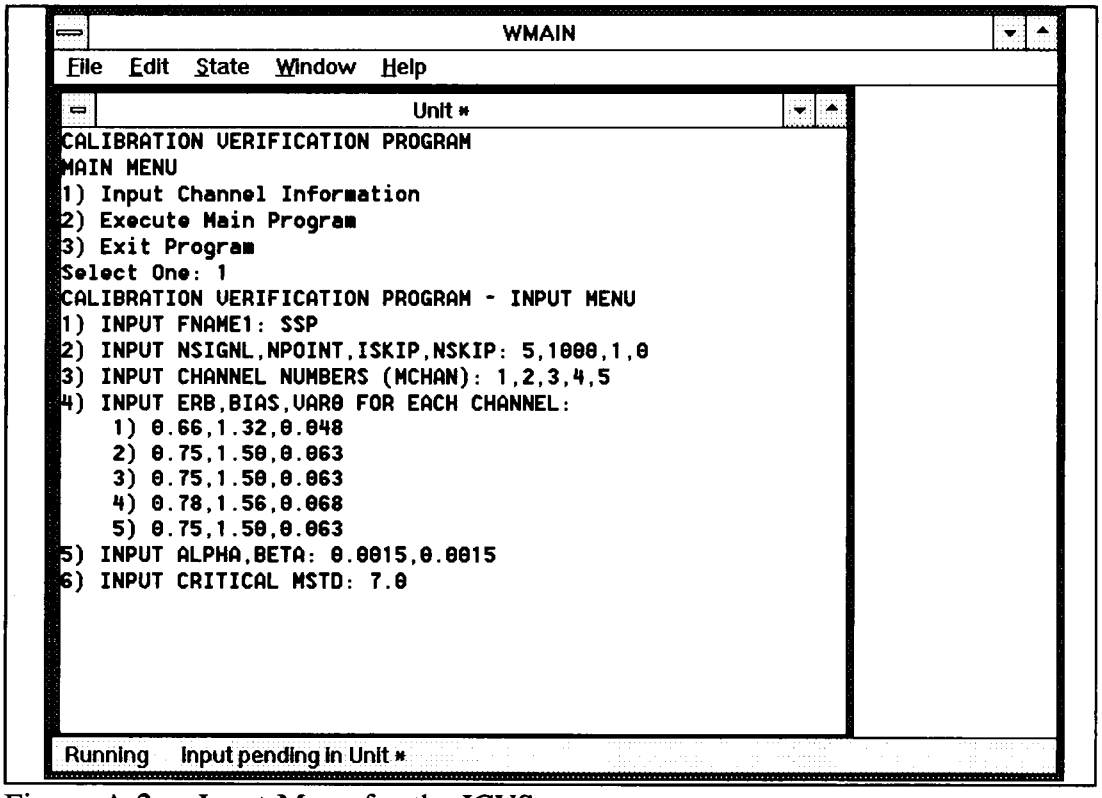


Figure A.2 Input Menu for the ICVS.

item asks for the measurement data file name. (In this example, the name "SSP" corresponds to the steady-state measurement file "SSP.DAT" and the sample file "SSP.SAM".) Item 2) asks for the number of signals to be analyzed (NSIGNL), the number of samples to be analyzed (NPOINT), a skipping factor (ISKIP) that allows samples to be skipped during the analysis (i.e., analyze every ISKIP sample), and a initial skipping factor (NSKIP) that allows the analysis to at the NSKIP sample. The third item asks for the channel numbers to be analyzed (MCHAN). The channel numbers correspond to the sequential order that the channels appear in the data files. Input 4) asks for the tolerances to be used in the GCC algorithm (ERB) and the SPRT algorithm (BIAS and VAR0) for each analyzed sensor. ERB is the error bound of a normal sensor as given by b_i and b_j in Equation (3.1). In this example it is evaluated as three times the standard deviation of a normal sensor. BIAS is the maximum allowable bias of a sensor used as given by μ_j in Equation (4.13). It corresponds to the difference of the mean values for the normal and the degraded distributions used in the SPRT. In this example, it is evaluated as six times the standard deviation of a normal sensor. VAR0 is the calculated variance for a normal sensor, and is used as shown in Equation (4.13). Input 5) allows the user to set the missed and false alarm probabilities used in the acceptance criteria for the SPRT (see Equations (4.6a) and (4.6b)). Note that the selection of α and β must be consistent with the selection of BIAS and VAR0 as discussed in Chapter 4. Finally, item 6) asks for the critical value of the Mean Samples To Decision (MSTD). The critical value of the MSTD is used in the indices for the MSTDN and MSTDD, and correspond to the point at which the

values of MSTDN and MSTDD are approximately equal. After the input data is complete, the Main Menu reappears. Selection 2) is then chosen to execute the program. The program may be terminated by choosing item 3), or by closing the window "WMAIN" at any time.

Results of the ICVS Program

The results of the ICVS program are placed in a set of child windows as illustrated in Figures (A.3) and (A.4). During execution of the program, four child windows appear labeled as 1) CALCULATED ESTIMATE, 2) LOG LIKELIHOOD RATIO, 3) INCONSISTENCY INDEX, and 4) SAMPLES EXCLUDED. Window 1) contains the sample number and the corresponding GCC estimate. The second window contains the value of the log likelihood ratio for each sample (Λ_n in Equation (4.10)). Window 3) contains the cumulative inconsistency index for each sample (C_i and C_j in Equation (3.2). Finally, window 4) contains the value of the flag that indicates if a sensor was excluded from the GCC estimate for a given sample (a zero indicates inclusion in the estimate while a one indicates exclusion from the estimate). These four windows are continuously updated during the execution of the program. When the execution is completed, the window labeled CVS SUMMARY appears. This window contains the overall results for all the calculated parameters. Figure (A.4) shows this window expanded.

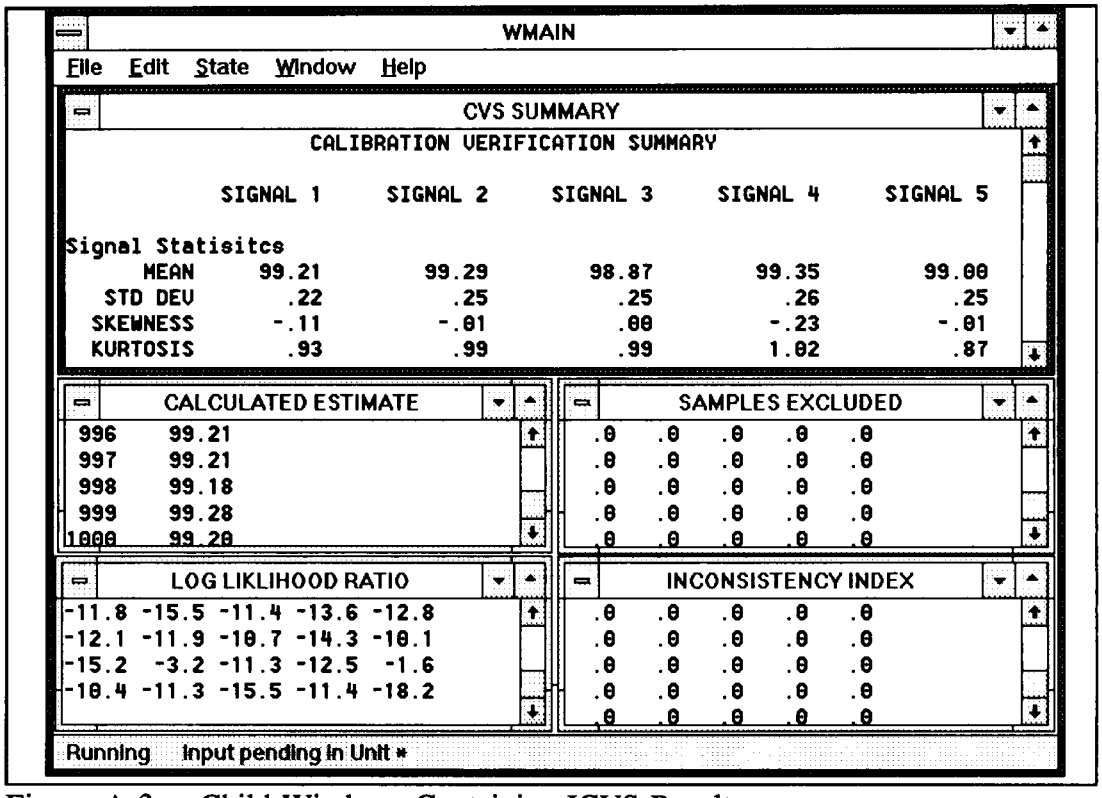


Figure A.3 Child Windows Containing ICVS Results

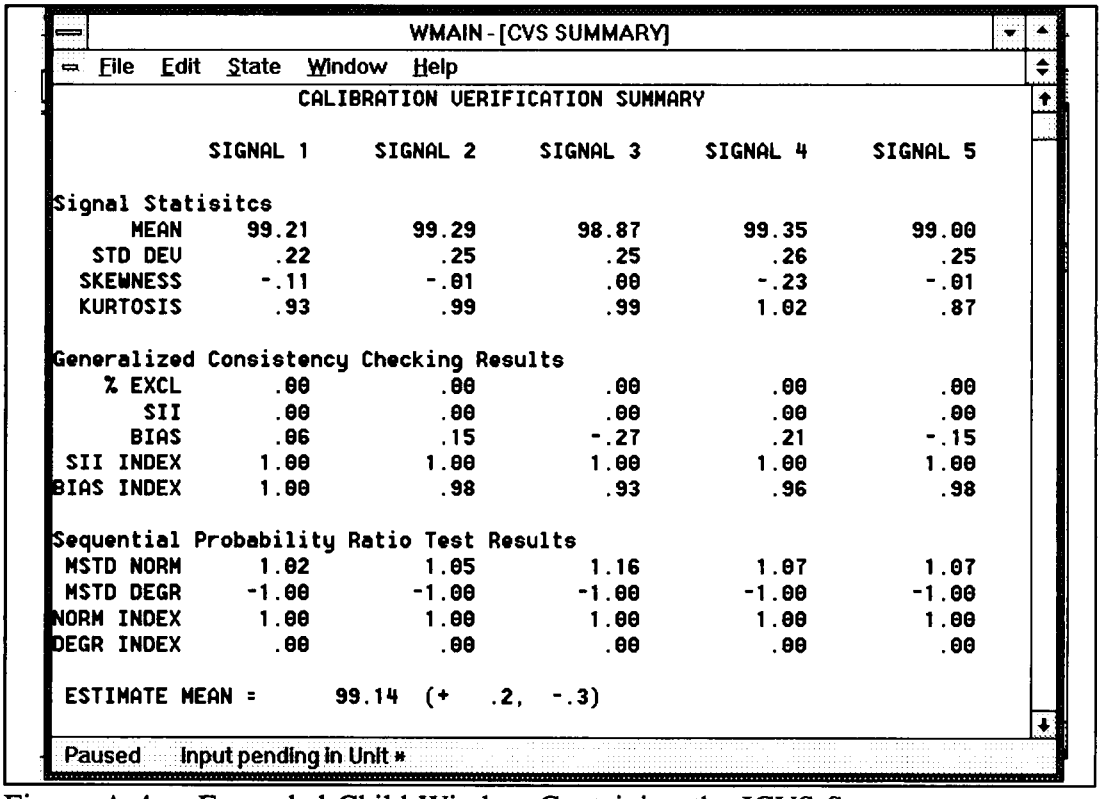


Figure A.4 Expanded Child Window Containing the ICVS Summary.

All of the data in these windows may be exported to other application programs. For example, the results in the CVS SUMMARY window may be pasted into a database program for tracking purposes. The results may be plotted using a spreadsheet or a chart program. For this example, I have created a set of spreadsheet templates to plot the results as a function of the sample number. These plots are shown in Figures (6.9) and (6.10) for the GCC estimate and the log likelihood ratios, respectively.

APPENDIX B - Listing of Code

```
C**** CALIBRATION VERIFICATION PROGRAM 1.0 - MS FORTRAN 5.1 - WINDOWS VERSION 3.1
C**** JOHN R. OLVERA - UNIVERSITY OF TENNESSEE - JANUARY 15, 1993

C**** INCLUDE FILE'S FOR MS WINDOWS DEFINITIONS

      INCLUDE 'FLIB.FI'
      INCLUDE 'FLIB.FD'

      RECORD /QWINFO/ WINFO

C**** DECLARATIONS

      COMMON /COM1/ NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP

      INTEGER*2 NCHAN,ISKIP,NSIGNL,NTOTAL,K,NPOINT,MCHAN(5),
     &NSKIP,DUMMY

      REAL ERB(5),VAR0(5),BIAS(5),NEXCL(5),MAXB,MINB,NSII(5)
     &,MSTDD(5),MSTDN(5),SII(5),SUM(5),SD(5),FUZBIAS(5),DEV(5)
     &,SKEW(5),KURT(5),FUZMSTDN(5),FUZMSTDD(5)

      CHARACTER*8 FNAME1

C**** CHILD WINDOW DATA STRUCTURE

      WINFO.TYPE=QWIN$SET

C**** ABOUT MESSAGE BOX

      DUMMY = ABOUTBOXQQ('Calibration Verification\r    Version 1.0'C)

C**** MAIN MENU - WRITE MENU TO UNIT *

200   CONTINUE

      WRITE(*,'(A)') ' CALIBRATION VERIFICATION PROGRAM'
      WRITE(*,'(A)') ' MAIN MENU'
      WRITE(*,'(A)') ' 1) Input Channel Information'
      WRITE(*,'(A)') ' 2) Execute Main Program'
      WRITE(*,'(A)') ' 3) Exit Program'

      WRITE(*,'(A\)') ' Select One: '

C**** INPUT SELECTION AND EXECUTION

      READ(*,*) ICH

C**** USER INPUTS

      IF (ICH .EQ. 1) THEN
          CALL CVINPUT(FNAME1,MCHAN,NCHAN,DELTAT
     &    ,ERB,BIAS,VAR0,BOUNDA,BOUNDB,ALPHA,BETA,CRITMSTD)

C**** EXECUTION OF ROUTINES

      ELSE IF (ICH .EQ. 2) THEN

          WINFO.X=0
          WINFO.Y=12
          WINFO.W=36
          WINFO.H=6
          OPEN(UNIT=30,FILE='USER',TITLE='CALCULATED ESTIMATE')

          DUMMY=SETWSIZEQQ(30,WINFO)

          WINFO.X=38
          WINFO.Y=0
          WINFO.W=42
          WINFO.H=6
          OPEN(UNIT=31,BLOCKSIZE=51200,FILE='USER',
     &     TITLE='LOG LIKLIHOOD RATIO')
```

```
            DUMMY=SETWSIZEQQ(31,WINFO)

            WINFO.X=38
            WINFO.Y=8
            WINFO.W=42
            WINFO.H=6
            OPEN(UNIT=32,FILE='USER',TITLE='INCONSISTENCY INDEX',
     &      BLOCKSIZE=51200)
            DUMMY=SETWSIZEQQ(32,WINFO)

            WINFO.X=38
            WINFO.Y=16
            WINFO.W=42
            WINFO.H=6
            OPEN(UNIT=33,FILE='USER',TITLE='SAMPLES EXCLUDED',
     &      BLOCKSIZE=51200)
            DUMMY=SETWSIZEQQ(33,WINFO)

            CALL CALVER(MCHAN,NCHAN,ERB,BIAS,VAR0,BOUNDA,NEXCL,
     &      BOUNDB,FNAME1,MSTDN,MSTDD,XMEAN,SII,SUM,SD,FUZBIAS,DEV,NSII,
     &      SKEW,KURT,FUZMSTDN,FUZMSTDD,CRITMSTD)

C**** MEASUREMENT SPAN

            MINB=DEV(1)
            MAXB=DEV(1)
            DO 220 I=2,NSIGNL
                IF (DEV(I) .GT. MAXB) THEN
                    MAXB=DEV(I)
                ELSE IF (DEV(I) .LT. MINB) THEN
                    MINB=DEV(I)
                ENDIF
220         CONTINUE

            WINFO.X=0
            WINFO.Y=0
            WINFO.W=42
            WINFO.H=10
            OPEN(UNIT=34,FILE='USER',TITLE='CVS SUMMARY')
            DUMMY=SETWSIZEQQ(34,WINFO)
            WRITE(34,500) 'CALIBRATION VERIFICATION SUMMARY'
            WRITE(34,501)
            WRITE(34,'(A)') ' '
            WRITE(34,'(A)') ' Signal Statisitcs'
            WRITE(34,502) 'MEAN',(SUM(L),L=1,NSIGNL)
            WRITE(34,502) 'STD DEV',(SD(L),L=1,NSIGNL)
            WRITE(34,502) 'SKEWNESS',(SKEW(L),L=1,NSIGNL)
            WRITE(34,502) 'KURTOSIS',(KURT(L),L=1,NSIGNL)
            WRITE(34,'(A)') ' '
            WRITE(34,'(A)') ' Generalized Consistency Checking Results'
            WRITE(34,502) '% EXCL',(NEXCL(L),L=1,NSIGNL)
            WRITE(34,502) 'SII',(SII(L),L=1,NSIGNL)
            WRITE(34,502) 'BIAS',(DEV(L),L=1,NSIGNL)
            WRITE(34,502) 'SII INDEX',(NSII(L),L=1,NSIGNL)
            WRITE(34,502) 'BIAS INDEX',(FUZBIAS(L),L=1,NSIGNL)
            WRITE(34,'(A)') ' '
            WRITE(34,'(A)') ' Sequential Probability Ratio Test Results'
            WRITE(34,502) 'MSTD NORM',(MSTDN(L),L=1,NSIGNL)
            WRITE(34,502) 'MSTD DEGR',(MSTDD(L),L=1,NSIGNL)
            WRITE(34,502) 'NORM INDEX',(FUZMSTDN(L),L=1,NSIGNL)
            WRITE(34,502) 'DEGR INDEX',(FUZMSTDD(L),L=1,NSIGNL)
            WRITE(34,503) 'ESTIMATE MEAN = ',XMEAN,'(+',MAXB,',',MINB,')'
            WRITE(34,'(A)') ' '
            WRITE(34,504) 'Input Data File: ',FNAME1
            WRITE(34,502) 'ERR. BOUND',(ERB(L),L=1,NSIGNL)
            WRITE(34,502) 'SPRT BIAS',(BIAS(L),L=1,NSIGNL)
            WRITE(34,505) 'VARIANCE',(VAR0(L),L=1,NSIGNL)
            WRITE(34,506) 'ALHPA = BETA = ',ALPHA


        ELSE IF (ICH .EQ. 3) THEN

            GOTO 205

        ENDIF

        GOTO 200
```

```
205   CONTINUE

500   FORMAT(20X,A32)
501   FORMAT('0',12X,'SIGNAL 1',5X,'SIGNAL 2',5X,'SIGNAL 3',5X,
     &'SIGNAL 4',5X,'SIGNAL 5')
502   FORMAT(' ',A10,2X,F8.2,5X,F8.2,5X,F8.2,5X,F8.2,5X,F8.2)
503   FORMAT('0',A17,F10.2,2X,A2,F5.1,A1,F5.1,A1)
504   FORMAT('0',A17,A8)
505   FORMAT(' ',A10,2X,E8.2,5X,E8.2,5X,E8.2,5X,E8.2,5X,E8.2)
506   FORMAT(' ',A15,E8.2)

      STOP
      END

C***  SUBROUTINE CALVER: CALIBRATION VERIFICATION METHODOLOGY
      SUBROUTINE CALVER(MCHAN,NCHAN,ERB,BIAS,VAR0,BOUNDA,NEXCL,BOUNDB,
     &FNAME1,MSTDN,MSTDD,XMEAN,SII,SUM,SD,FUZBIAS,DEV,NSII,SKEW,KURT,
     &FUZMSTDN,FUZMSTDD,CRITMSTD)

      COMMON /COM1/ NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP

      INTEGER*2 NCHAN,BSETTO0(5),ISAMPL,NMAX,IMAX,NPLACE(5),
     &IMIN,ITEST,MCHAN(5),NINCLP(5),JINCLP,DBIAS(5),NBIAS(5),
     &NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP

      REAL MEAS(5),ERB(5),DARRAY(5,3),VAR0(5),SPRTB(5),KURT(5),
     &BOUNDA,BOUNDB,BIAS(5),EXCL(5),NEXCL(5),SUM(5),FUZBIAS(5),SKEW(5)
     &,XESTMT,SII(5),TM(5,3000),SD(5),MSTDN(5),MSTDD(5),DEV(5),NSII(5)
     &,FUZMSTDN(5),FUZMSTDD(5),CRITMSTD,BAND

      INTEGER*4 JREC,IKREC


      CHARACTER*8 FNAME1

C***  INITIALIZE ARRAYS
      DO 5 K=1,NSIGNL
           SPRTB(K)=0.
           EXCL(K)=0.
           NEXCL(K)=0.
           NBIAS(K)=0.
           DBIAS(K)=0.
           SII(K)=0.
           NSII(K)=0.
           SD(K)=0.
           MSTDD(K)=0.
           MSTDN(K)=0.
           FUZBIAS(K)=0.
           FUZMSTDN(K)=0.
           FUZMSTDD(K)=0.
           DEV(K)=0.
           SKEW(K)=0.
           KURT(K)=0.
5     CONTINUE

      IRECL = 4*(4*NSIGNL+1)
      OPEN(3,FILE=FNAME1//'.DAT',STATUS='OLD',ACCESS='DIRECT',RECL=4)

C**** MAIN PROGRAM LOOP
      DO 10 ISAMPL=1,NTOTAL
           IKREC=ISKIP*(ISAMPL-1)+NSKIP+1
           DO 15 J=1,NSIGNL
                JREC=MCHAN(J)+(IKREC-1)*NCHAN
                READ(3,REC=JREC) MEAS(J)
                TM(J,ISAMPL)=MEAS(J)
15         CONTINUE

           K=NSIGNL

           DO 20 J=1,K
                DARRAY(J,1)=FLOAT(J)
                EXCL(J)=0.
20         CONTINUE
800        CONTINUE

C***  FIND DEGREE OF INCONSISTENCY FOR K MEASUREMENTS
```

```
            IF(K .GT. 1) THEN
                 CALL INCONSIS(MEAS,ERB,ITEST,DARRAY)
            ELSE
                 IF(PESTMT .EQ. 0) THEN
                     XESTMT = DARRAY(1,2)
                 ELSE
                     XESTMT = PESTMT
                 ENDIF

                 DO 30 J=2,NSIGNL
                      IS=DARRAY(J,1)
                      EXCL(IS)=1.
30               CONTINUE
                 GOTO 900
            ENDIF

C***   TEST FOR INCONSISTENT PAIRS

            IF(ITEST .EQ. 0) THEN
                 CALL ESTMAT(XESTMT,DARRAY)
                 IF (K .EQ. NSIGNL) THEN
                      GOTO 900
                 ELSE
                      DO 35 J=K+1,NSIGNL
                           IS = DARRAY(J,1)
                           EXCL(IS)=1.
35                    CONTINUE
                      GOTO 900
                 ENDIF
            ENDIF
700         CONTINUE

C***   REORDER DARRAY(I,J) FOR INCREASING DARRAY(I,3)

            CALL REORDER(NMAX,IMAX,IMIN,DARRAY)
            IF(IMAX .EQ. 0) THEN
                 CALL ESTMAT(XESTMT,DARRAY)
                 IF(K .EQ. NSIGNL) THEN
                      GOTO 900
                 ELSE
                      DO 40 J=K+1,NSIGNL
                           IS=DARRAY(J,1)
                           EXCL(IS)=1.
40                    CONTINUE
                      GOTO 900
                 ENDIF
            ELSEIF(IMIN .EQ. 0) THEN
                 CALL ESTMAT(XESTMT,DARRAY)
                 IF(K .EQ. NSIGNL) THEN
                      GOTO 900
                 ELSE
                      DO 45 J=K+1,NSIGNL
                           IS=DARRAY(J,1)
                           EXCL(IS)=1.
45                    CONTINUE
                      GOTO 900
                 ENDIF
            ELSEIF(IMAX .EQ. K-1) THEN
                 IF(K .EQ. NMAX) THEN
                      CALL PASTEST(ERB,XESTMT,PESTMT,NINCLP,JINCLP,
     &                 DARRAY)
                      IF(JINCLP .EQ. 0) THEN
                           DO 50 L=1,K
                                DARRAY(L,3)=FLOAT(K)-1.
50                         CONTINUE
                           DO 55 J=1,NSIGNL
                                IS=DARRAY(J,1)
                                EXCL(IS)=1.
55                         CONTINUE
                           GOTO 910
                      ENDIF
                      K=JINCLP
                      DO 60 J=1,NSIGNL
                           DO 65 L=1,JINCLP
                                IF(J .EQ. NINCLP(L)) GOTO 60
65                         CONTINUE
                           IS = DARRAY(J,1)
```

```
                        EXCL(IS) = 1.
60                  CONTINUE
                    GOTO 900
               ELSE
                    K=K-NMAX
                    DO 70 L=1,K
                        DARRAY(L,3) = DARRAY(L,3) - NMAX
70                  CONTINUE
                    GOTO 700
               ENDIF
          ELSEIF(NMAX .EQ. 1) THEN
               K=K-NMAX
               GOTO 800
          ELSEIF(K .EQ. NMAX) THEN
               CALL PASTEST(ERB,XESTMT,PESTMT,NINCLP,JINCLP,
     &         DARRAY)
               IF(JINCLP .EQ. 0) THEN
                    DO 75 L=1,K
                        DARRAY(L,3)= FLOAT(K)-1.
75                  CONTINUE
                    DO 80 J=1,NSIGNL
                        IS=DARRAY(J,1)
                        EXCL(IS)=1.
80                  CONTINUE
                    GOTO 910
               ENDIF
               K=JINCLP
               DO 85 J=1,NSIGNL
                    DO 90 L=1,JINCLP
                        IF(J .EQ. NINCLP(L)) GOTO 85
90                  CONTINUE
                    IS=DARRAY(J,1)
                    EXCL(IS)=1.
85             CONTINUE
               GOTO 900
          ELSE
               K=K-NMAX
               GOTO 800
          ENDIF
900       CONTINUE
          CALL SEQBIAS(XESTMT,SPRTB,VAR0,BIAS,BSETTO0,BOUNDA,
     &    BOUNDB,DARRAY)
910       CONTINUE

          DO 95 L=1,NSIGNL
               NSID=DARRAY(L,1)
               DO 100 J=1,NSIGNL
                    IF(NSID .EQ. J) NPLACE(J)=L
100            CONTINUE
95        CONTINUE

          WRITE(30,510) ISAMPL, XESTMT
          WRITE(31,511) (SPRTB(L), L=1,NSIGNL)
          WRITE(32,512) (DARRAY(NPLACE(L),3), L=1,NSIGNL)
          WRITE(33,512) (EXCL(L), L=1,NSIGNL)

          DO 105 L=1,NSIGNL

               IF(SPRTB(L) .GE. BOUNDB) DBIAS(L)=DBIAS(L)+1
               IF(SPRTB(L) .LE. BOUNDA) NBIAS(L)=NBIAS(L)+1
               IF(BSETTO0(L) .EQ. 1) SPRTB(L)=0.
               NEXCL(L)=NEXCL(L)+EXCL(L)
               SII(L)=SII(L) + DARRAY(NPLACE(L),3)

               SUM(L)=SUM(L)+MEAS(L)

               DEV(L)=DEV(L)+MEAS(L)-XESTMT

105       CONTINUE

          PESTMT=XESTMT
          XTOT = XTOT + XESTMT

10    CONTINUE

C**** SUMMARY OUTPUTS
```

```
      XMEAN = XTOT/NTOTAL

      DO 115 I=1,NSIGNL

C****MEAN SIGNAL INCONSISTENCY INDEX
C          BAND = NSIGNL-1
           BAND = 1.0
           SII(I)=SII(I)/NTOTAL
           IF(SII(I) .LE. BAND) THEN
               NSII(I) = 1-(2./(2*BAND)**2)*SII(I)**2
           ELSEIF(SII(I) .LE. 2*BAND) THEN
               NSII(I)=(2./(2*BAND)**2)*
     &          (SII(I)-2*BAND)**2
           ELSE
               NSII(I) = 0.
           ENDIF

C****PERCENT OF SAMPLES SIGNAL WAS EXCLUDED FROM ESTIMATE

           NEXCL(I)=100*NEXCL(I)/NTOTAL

C****MEAN OF MEASURED SIGNALS

           SUM(I)=SUM(I)/NTOTAL

C****STANDARD DEVIATION OF MEASURED SIGNALS

           DO 125 J=1,NTOTAL
               SD(I)=SD(I)+(TM(I,J)-SUM(I))**2
125        CONTINUE
           SD(I)=(SD(I)/NTOTAL)**(0.5)

C****SKEW AND KURTOSIS OF MEASURED SIGNALS

           DO 135 J=1,NTOTAL
               SKEW(I)=SKEW(I)+(TM(I,J)-SUM(I))**3
               KURT(I)=KURT(I)+(TM(I,J)-SUM(I))**4
135        CONTINUE
           SKEW(I) = SKEW(I)/(NTOTAL*SD(I)**3)
           KURT(I) = KURT(I)/(3*NTOTAL*SD(I)**4)

C****MEAN # SAMPLES TO SPRT DECISION - NORMAL (MSTDN)

           IF(NBIAS(I) .GT. 0) THEN
               MSTDN(I)=FLOAT(NTOTAL)/NBIAS(I)
               IF(MSTDN(I) .LT. CRITMSTD) THEN
                   FUZMSTDN(I) = 1-((MSTDN(I)-1)**2)*2/
     &                ((2*(CRITMSTD-1))**2)
               ELSEIF(MSTDN(I) .LT. 2*CRITMSTD) THEN
                   FUZMSTDN(I) = ((MSTDN(I)-1-2*(CRITMSTD-1))**2)*2/
     &                (2*(CRITMSTD-1))**2
               ELSE
                   FUZMSTDN(I) = 0.0
               ENDIF
           ELSE
               MSTDN(I) = -1.
               FUZMSTDN(I)=0.
           ENDIF

C****MEAN # SAMPLES TO SPRT DECISION - DEGRADED (MSTDD)

           IF(DBIAS(I) .GT. 0) THEN
               MSTDD(I)=FLOAT(NTOTAL)/DBIAS(I)
               IF(MSTDD(I) .LT. CRITMSTD) THEN
                   FUZMSTDD(I) = 1-((MSTDD(I)-1)**2)*2/
     &                ((2*(CRITMSTD-1))**2)
               ELSEIF(MSTDD(I) .LT. 2*CRITMSTD) THEN
                   FUZMSTDD(I) = ((MSTDD(I)-1-2*(CRITMSTD-1))**2)*2/
     &                (2*(CRITMSTD-1))**2
               ELSE
                   FUZMSTDD(I) = 0.0
               ENDIF
           ELSE
               MSTDD(I) = -1.
               FUZMSTDD(I) = 0.0
           ENDIF
```

```
C****MEAN DEVIATION FROM ESTIMATE

          DEV(I)=DEV(I)/NTOTAL
          IF(DEV(I) .LE. -2*ERB(I)) THEN
              FUZBIAS(I) = 0.
          ELSEIF(DEV(I) .LE. -ERB(I)) THEN
              FUZBIAS(I)=(2/((2*ERB(I))**2))*(DEV(I)+2*ERB(I))**2
          ELSEIF(DEV(I) .LE. 0) THEN
              FUZBIAS(I)=1-(2/((2*ERB(I))**2))*(DEV(I)**2)
          ELSEIF(DEV(I) .LE. ERB(I)) THEN
              FUZBIAS(I)=1-(2/((2*ERB(I))**2))*(DEV(I)**2)
          ELSEIF( DEV(I) .LE. 2*ERB(I)) THEN
               FUZBIAS(I)=(2/((2*ERB(I))**2))*(DEV(I)-2*ERB(I))**2
          ELSE
              FUZBIAS(I) = 0.
          ENDIF

115   CONTINUE

510   FORMAT(' ',I4,1X,F8.2)
511   FORMAT(' ',F5.1,1X,F5.1,1X,F5.1,1X,F5.1,1X,F5.1)
512   FORMAT(' ',F4.1,1X,F4.1,1X,F4.1,1X,F4.1,1X,F4.1)


      CLOSE(1)
      CLOSE(3)

      RETURN
      END
C
C***   SUBROUTINES USED IN MAIN PROGRAM OF THE GENERALIZED CONSISTENCY CHECKING
C***   AND SEQUENTIAL PROBABILITY RATIO TEST (SVSUB.FOR 3/22/88)
C
      SUBROUTINE INCONSIS(MEAS,ERB,ITEST,DARRAY)

      COMMON /COM1/ NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP

      INTEGER*2 INDEX(5),ITEST,NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP
      REAL DARRAY(5,3),MEAS(NSIGNL),ERB(NSIGNL)


      DO 10 J=1,NSIGNL
 10   INDEX(J)=0
C
C***  PAIRWISE COMPARISON OF ALL MEASUREMENTS; INCREASE THE ERROR INDECES
C***  OF BOTH SENSORS BY 1 IF THE PAIR IS INCONSISTENT:
C
      DO 20 J=1,K-1
         JS=DARRAY(J,1)
         DO 30 L=J+1,K
            LS=DARRAY(L,1)
            IF(ABS(MEAS(JS)-MEAS(LS)).GT.ERB(JS)+ERB(LS)) THEN
               INDEX(JS)=INDEX(JS)+1
               INDEX(LS)=INDEX(LS)+1
            ENDIF
  30     CONTINUE
 20    CONTINUE
C
C***  SET UP A 2-D ARRAY D(J,L) WHERE ITS FIRST ARGUMENT (J=1,...,K) DENOTES
C***  THE PLACES IN THE ROW, AND THE SECOND ARGUMENT (L=1,2,3) GIVES THE
C***  ORIGINAL SENSOR ORDER (SENSOR ID NUMBER), THE MEASURED VALUE, AND THE
C***  ERROR INDEX OF THE SENSOR LOCATED AT THE PLACE J IN THE ACTUAL ORDER.
C
      DO 40 J=1,K
         JS=DARRAY(J,1)
         DARRAY(J,2)=MEAS(JS)
         DARRAY(J,3)=INDEX(JS)
 40   CONTINUE
C
C***  SUM OF ERROR INDECES FOR THE CURRENT COMPARISON: ITEST
C
      ITEST=0
      DO 50 J=1,K
 50   ITEST=ITEST+INDEX(J)
      RETURN
      END
C
```

```
C
C
      SUBROUTINE REORDER(NMAX,IMAX,IMIN,DARRAY)

      COMMON /COM1/ NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP

      INTEGER*2 NMAX,IMAX,IMIN,JMIN,NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP
      REAL DARRAY(5,3)
C
C***  REARRANGE THE SENSORS WITH INCREASING ERROR INDECES
C
      DO 10 L = 1,K-1
         JMIN=L
         DO  20 J = L+1,K
             IF(DARRAY(J,3).LT.DARRAY(JMIN,3)) JMIN=J
 20      CONTINUE
         TEMP1=DARRAY(L,1)
         TEMP2=DARRAY(L,2)
         TEMP3=DARRAY(L,3)
         DARRAY(L,1)=DARRAY(JMIN,1)
         DARRAY(L,2)=DARRAY(JMIN,2)
         DARRAY(L,3)=DARRAY(JMIN,3)
         DARRAY(JMIN,1)=TEMP1
         DARRAY(JMIN,2)=TEMP2
         DARRAY(JMIN,3)=TEMP3
 10   CONTINUE
      DO  30 J = 1,K
         JS=DARRAY(J,1)
 30   CONTINUE
      IMAX=DARRAY(K,3)
      IMIN=DARRAY(1,3)
      NMAX=0
      DO  40 L = K,1,-1
          IF(DARRAY(L,3).EQ.DARRAY(K,3)) THEN
               NMAX=NMAX+1
          ELSE
               GOTO 50
          ENDIF
 40   CONTINUE
 50   CONTINUE
      RETURN
      END
C
      SUBROUTINE ESTMAT(XESTMT,DARRAY)

      COMMON /COM1/ NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP

      INTEGER*2 NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP
      REAL DARRAY(5,3),XESTMT

      SUM1=0.
      SUM2=0.
      DO  10 J = 1,K

         IF(DARRAY(J,3) .LT. float(K-1)/2) THEN
           SUM1=SUM1+(1-(2./((K-1)**2))*DARRAY(J,3)**2)*DARRAY(J,2)
           SUM2=SUM2+(1-(2./((K-1)**2))*DARRAY(J,3)**2)
         ELSE
           SUM1=SUM1+((2./((K-1)**2))*(K-1-DARRAY(J,3))**2)*DARRAY(J,2)
           SUM2=SUM2+((2./((K-1)**2))*(K-1-DARRAY(J,3))**2)
         ENDIF

10    CONTINUE

      XESTMT=SUM1/SUM2
      RETURN
      END
C
C
C
      SUBROUTINE PASTEST(ERB,XESTMT,PESTMT,NINCLP,JINCLP,DARRAY)

      COMMON /COM1/ NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP

      INTEGER*2 NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP,
     &NINCLP(NSIGNL),JINCLP,JEXCLP,IS
```

```
      REAL ERB(NSIGNL),DARRAY(5,3),XESTMT

      JINCLP=0
      JEXCLP=0
c      DO  10  L = 1,K
c          IS=DARRAY(L,1)
c          IF(ABS(DARRAY(L,2)-PESTMT).LE.ERB(IS)) THEN
c              JINCLP=JINCLP+1
c              NINCLP(JINCLP)=L
c          ENDIF
c 10   CONTINUE
c
c      IF(JINCLP.EQ.0) THEN
         XESTMT=PESTMT
c      ELSE
c          W=1.
c          SUM1=0.
c          SUM2=0.
c          DO  30 L = 1,JINCLP
c              SUM1=W*DARRAY(NINCLP(L),2)+SUM1
c              SUM2=SUM2+W
c 30       CONTINUE
c          XESTMT=SUM1/SUM2
c      ENDIF

      RETURN
      END
C
C
C
      SUBROUTINE SEQBIAS(XESTMT,SPRTB,VAR0,BIAS,BSETTO0,BOUNDA,
     &BOUNDB,DARRAY)

      COMMON /COM1/ NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP

      INTEGER*2 NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP,BSETTO0(NSIGNL),
     & ISIG(5),IS
      REAL SPRTB(NSIGNL),DARRAY(5,3),BIAS(NSIGNL),VAR0(NSIGNL),X(5),
     &XESTMT,BOUNDA,BOUNDB
C
C***  SET UP AN ARRAY CONTAINING THE DEVIATION OF SIGNAL NO. DARRAY(I,1)
C***  FROM XESTMT :    DARRAY(I,2)-XESTMT,      I = 1, ... ,NSIGNL
C
      DO 10  J = 1,NSIGNL
         ISIG(J) = DARRAY(J,1)
         X(ISIG(J)) = ABS(DARRAY(J,2)-XESTMT)
         BSETTO0(J) = 0
 10   CONTINUE
      DO 30  J = 1,NSIGNL
         IS = ISIG(J)
         SPRTB(IS)=SPRTB(IS)+BIAS(IS)*(X(IS)-BIAS(IS)/2.)/VAR0(IS)
 30   CONTINUE
C
C***  TEST IF DECISION BOUND REACHED BY SPRTB.
C
      DO  40 J = 1,NSIGNL
          IS=ISIG(J)
          IF(SPRTB(IS).GT.BOUNDB) THEN
              BSETTO0(IS)=1
          ENDIF
          IF(SPRTB(IS).LT.BOUNDA) THEN
             BSETTO0(IS)=1
          ENDIF
 40   CONTINUE
      RETURN
      END
C
C
C


      SUBROUTINE CVINPUT(FNAME1,MCHAN,NCHAN,DELTAT,ERB,BIAS,VAR0,
     &                   BOUNDA,BOUNDB,ALPHA,BETA,CRITMSTD)


      COMMON /COM1/ NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP

      INTEGER*2 NSIGNL,NTOTAL,K,NPOINT,ISKIP,NSKIP,MCHAN(5),NCHAN
```

```
      REAL ERB(5),VAR0(5),BIAS(5),DELTAT,BOUNDA,BOUNDB,CRITMSTD
      CHARACTER*8 FNAME1

      WRITE(*,'(A)') ' CALIBRATION VERIFICATION PROGRAM - INPUT MENU'

      WRITE(*,'(A\)') ' 1) INPUT FNAME1: '
      READ(*,'(A)') FNAME1

      WRITE(*,'(A\)') ' 2) INPUT NSIGNL,NPOINT,ISKIP,NSKIP: '
      READ(*,*) NSIGNL,NPOINT,ISKIP,NSKIP

      WRITE(*,'(A\)') ' 3) INPUT CHANNEL NUMBERS (MCHAN): '
      READ(*,*) (MCHAN(J),J=1,NSIGNL)

      WRITE(*,'(A)') ' 4) INPUT ERB,BIAS,VAR0 FOR EACH CHANNEL: '
      DO 10 L=1,NSIGNL
           WRITE(*,400) L
           READ(*,*) ERB(L),BIAS(L),VAR0(L)
10    CONTINUE

      WRITE(*,'(A\)') ' 5) INPUT ALPHA,BETA: '
      READ(*,*) ALPHA,BETA
      BOUNDA=LOG(BETA/(1.-ALPHA))
      BOUNDB=LOG((1.-BETA)/ALPHA)

      WRITE(*,'(A\)') ' 6) INPUT CRITICAL MSTD: '
      READ(*,*) CRITMSTD

      NTOTAL=IFIX(FLOAT(NPOINT)/FLOAT(ISKIP))
      OPEN(15,FILE=FNAME1//'.SAM',ACCESS='DIRECT',RECL=4)
      READ(15,REC=1) NCHAN
      READ(15,REC=3) DELTAT
      CLOSE(15)
400   FORMAT(5X,I1,') ',\)
      RETURN
      END
```

VITA

John Olvera graduated from Northwestern University in Evanston, Illinois in 1981 with a Bachelor of Science in Nuclear Engineering. From 1981 through 1984, he was employed by the Tennessee Valley Authority as a safety analysis engineer. Mr. Olvera then worked for one and a half years as a start-up engineer in the Power Ascension Test Group at the Wolf Creek Generating Station. He then spent two years as a project engineer at the Point Beach Nuclear Plant. In 1988 and 1989 he attended the University of Tennessee in the Master of Science program in nuclear engineering. From 1990 through 1992, Mr. Olvera worked for JBF Associates of Knoxville, Tennessee as a risk analyst in the chemical process industry. He returned to the University of Tennessee in 1993 to complete the M.S. thesis, and is currently pursuing a Doctorate in nuclear engineering.