ON-LINE FAULT DIAGNOSIS IN A NUCLEAR REACTOR BY SEQUENTIAL TESTING

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Summary

A sequential test technique for on-line fault diagnosis of sensor signals has been developed and successfully demonstrated in an operating nuclear reactor. The methodology provides a systematic procedure for detection and isolation of sensor failures by taking into account consistencies among all available measurements of a given process variable. Fault diagnosis is accomplished on the basis of the cumulative information derived from the measurement history that includes the past and current observations.

Introduction

Validity and accuracy of sensor signals are crucial for the enhancement of safety, reliability, and performance of complex industrial processes such as nuclear power plants. When a failure of a critical measuring device occurs, it is essential to have some means to generate an alarm with the least possible delay. On the other hand, a false alarm, i.e., detecting a fault when none has really occurred, is very undesirable because it diminishes the credibility of the fault diagnosis procedure and it may cause the removal of a normally functioning device from on-line operation. A trade-off between these two requirements, i.e., detection speed and occurrence of false alarms can be achieved by appropriate processing of sensor outputs, where the decisions on device failures are made on the basis of the measurement history that includes both past and current observations.[1-4]

If multiply redundant sensors are available for the measurement of a process variable such as the safety-related parameters in a nuclear power plant, the sensor failure(s) can be detected by inconsistencies among these redundant measurements, except for the common-mode failures where all sensors fail simultaneously and identically. Additional information is needed to detect the common mode failures and it is usually available from other sources. Upon detection of a failure, the problem then is fault isolation, i.e., determination of which sensor is failed. This requires a systematic search for the normally functioning sensors from a given set of redundant sensors, thereby isolating the abnormal ones.

Recently, Desai and Ray[5] have developed an on-line signal validation methodology that performs fault detection and isolation (FDI) on the basis of a concurrent checking of the consistencies of subsets of the total set of redundant measurements of a given process variable. The goal of this paper is to develop a sequential test procedure for on-line fault diagnosis in a set of redundant sensors in the framework of the aforesaid FDI methodology and to demonstrate its applicability to nuclear power plants. As a proof-of-concept, the sequential test procedure has been verified for on-line detection and isolation of sensor failures in the 5 MWt nuclear reactor presently in operation at MIT, Cambridge, Massachusetts.

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Background

The fault detection and isolation methodology seeks out the largest consistent subset from a set of redundant sensors. The consistency between two sensors measuring the same variable implies that their outputs differ by less than the sum of the allowable errors in their outputs. Allowable errors or error bounds, specific to individual sensors, can be obtained from the information on tolerances due to calibration, nonlinearities, scale factor errors, etc., that are usually available from the manufacturer's specifications. As the number of redundant sensors increases, the checking of consistency in all possible combinations and the attendant task of bookkeeping for all information at the current and past sampling instants become very complex. A systematic, unified procedure, appropriate for a digital processor, that relies on recursive relations, based on the consistencies of each sensor relative to the remaining ones, has been developed for diagnosing sensor failures. A mathematical background of the test procedure is given in the Appendix where Section A.1 is devoted to the development of the FDI technique on the basis of the "parity space" concept[6] and the sequential test algorithm that forms an important part of the technique is presented in Section A.2.

The FDI technique is adaptable for on-line applications with mini- and microcomputers. The memory requirement is small, and very few multiplicative arithmetic operations are involved for fault diagnostics and measurement estimation. In contrast, other FDI methods[7-9] need to solve a number of differential equations for recursive filters that require relatively larger computations, and the FDI decisions are more vulnerable to modelling errors due to changes in the assumed plant characteristics.

FDI decisions can be made from the observations derived from either a single sample or a time history of multiple samples. The decisions based on a single sample, i.e., decisions which disregard the past performance, are reliable only if the magnitudes of the errors in the affected sensors are large in comparison to the measurement noise and uncertainty. In a nuclear plant, a moderate degradation of sensors such as calibration errors for long-term operations may not be reliably detected by single-sample decisions without incurring unacceptable probabilities of false alarms. In such cases, FDI decisions should be made on the basis of multiple observations that make use of the cumulative information provided by the measurement history from the past and current samples rather than relying solely on the current sample. A sequential decision-making procedure to achieve this goal is

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presented in Section A.2 of the Appendix.

In general, the cost function for a decision rule is made up of two opposing requirements, namely, minimizing the probability of false alarms as well as the time delay in fault detection. For an optimal decision rule, the cost function is minimized such that the best trade-off is achieved between the aforementioned requirements. Wald's sequential probability ratio test (SPRT)[1] is optimal in the sense that the expected value of the number of samples required for making a decision between two fixed hypotheses, whether the system is in the normal or degraded mode, is minimum for specified probabilities of incorrect decisions. Thus it achieves the best tradeoff between them to make a decision and the accuracy of the decision. Wald's test is devised on the assumption that either one or the other of the two hypotheses holds while the test is running. This restriction is removed in the disruption test of Shiryaeyev[2] where the probability of a change in the hypothesis at any sampling instant is taken into account, and the decision as to whether a transition has occurred from the normal to the degraded mode is made on the basis of a posteriori probability of failure derived from the past and current observations. In contrast to Wald's test, Shiryaeyev's test provides a smaller expected value of delays in fault detection at the expense of increased computations. Chien et al.[3] developed a suboptimal method for on-line fault detection in navigational system sensors, that is computationally efficient and preserves the improved features of Shiryaeyev's test. In this paper, a sequential test procedure has been designed in the framework of Chien's approach for diagnosis of sensor failures in nuclear power plants.

Application of the Sequential Test Methodology In A Nuclear Reactor

System Description

A description of the system configuration and instrumentation of the 5 MWt fission reactor is given in the MITR-II Reactor Systems Manual.[10] The reactor is heavy-water reflected, light-water moderated and cooled, and functions as a research and educational facility. It is a tank-type reactor, similar to a PWR except that it operates at atmospheric pressure and its coolant temperature is 55°C or less. A simplified diagram of the process and instrumentation is given in Figure 1.

The nuclear instrumentation used for the research described in this paper consists of three neutron flux sensors and a gamma-ray sensor that correlates neutron power with the radioactivity (N^{16}) of the primary coolant. Four independent measurements of primary coolant flow are obtained from the pressure differences across orifices. Primary coolant temperatures are measured as follows: two sensors for the hot leg, two sensors for the cold leg, and one sensor for temperature difference between the legs. In effect, three measurements are available for the temperature difference. The noise and statistical characteristics of the MITR-II's flow, temperature, and neutron flux instrumentation are similar to those in commercial reactors. These sensors are hard-wired to a portable LSI-11/23 minicomputer through appropriate isolators, signal conditioners, and A/D converters. None of the sensors that form the MITR-II's safety system were used for this research.

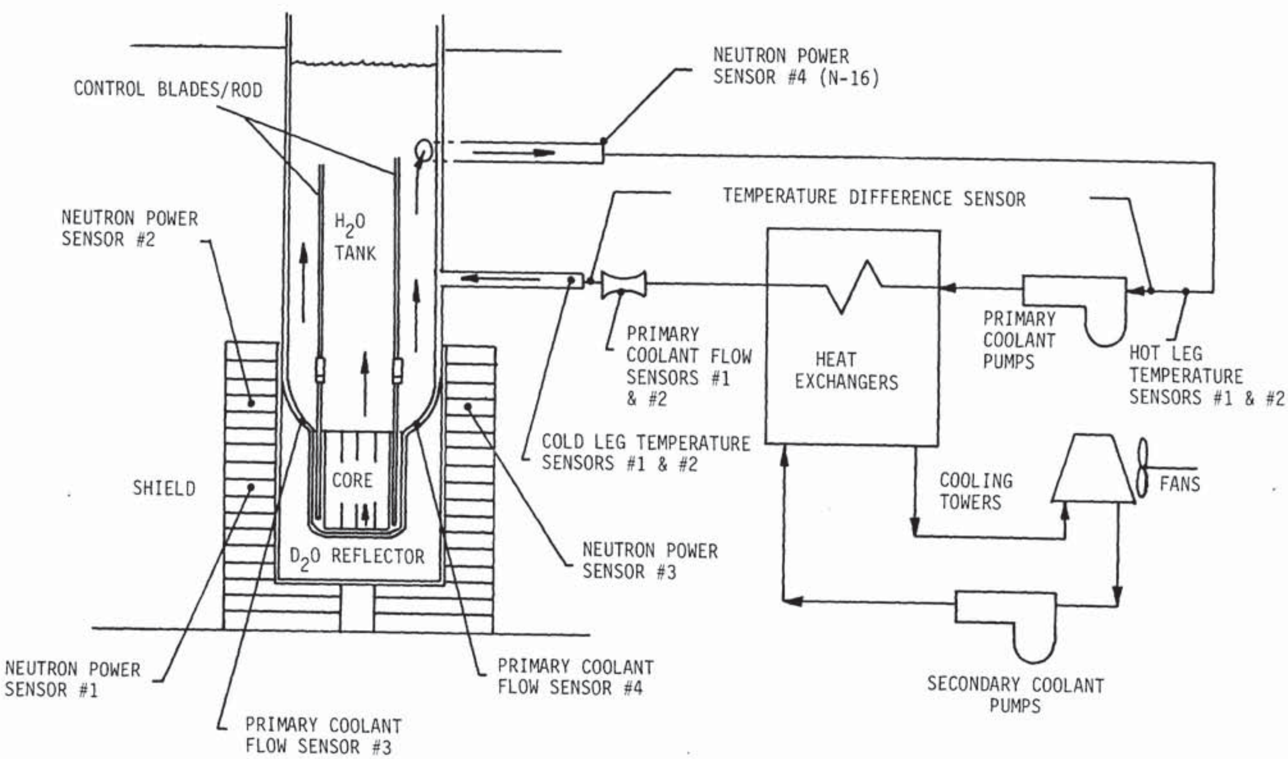

Figure 1. Simplified Process and Instrumentation Diagram for MITR-II

Results and Discussion

The sequential procedure was tested in the MITR-II for on-line fault diagnosis of sensor signals. The salient features of the procedure can be summarized as follows: Given ℓ sensors and their error bounds, the consistency/inconsistency of the $\ell(\ell-1)/2$ pairs are determined by the sequential test algorithm presented in Section A.2 of the Appendix; this information is used for on-line detection and isolation of sensor failures by application of the FDI technique described in Section A.1 of the Appendix.

The machine-executable form of the program on an LSI-11/23 microcomputer requires a memory of approximately 20 kilobytes that include the libraries of FORTRAN and special real-time routines. The execution time is less than 130 milliseconds per cycle if no messages are generated. Therefore, sampling frequencies were chosen in the range of 0.2 hz to 5 hz, and the choices were made depending on the volume of the message display such that the sampling periods were not exceeded.

The error bounds for the sensors can be evaluated either by analyzing the test data or from the information on tolerances due to calibration, nonlinearity, scale factor, etc., available from the instrument manufacturers. At different power levels of MITR-II, steady-state data for all measurements were collected and analyzed for evaluating the noise statistics; the results showed that the measurement noise is practically independent of the reactor power level. The expected values and covariance matrices of power, flow, and temperature difference (ΔT) measurements at full load are listed in Table I, which shows that the measurements are correlated, indicating the possible presence of process noise. On the basis of the analyzed data, spatial location, and manufacturer's specifications, the error bounds for all operating conditions were chosen in the range of 0.05 to 0.25 MW, 0.5 to 2.0 kg/s, and 0.3 to 0.5°C for neutron power, primary coolant flow, and temperature difference measurements, respectively. The error bounds for individual sensors can be dynamically compensated to account for process changes. For example, the error bound for the gamma ray sensor (see the System Description section and Figure 1) is designed to be relaxed under transient conditions to prevent possible false alarms by taking into consideration a half life of 7.4 sec for N^{16} and the transport delay due to coolant flow within the core tank, whereas the remaining three power sensors are assigned invariant error bounds.

The MITR-II is started and shut down every week. A series of tests were conducted during the week days with different values of mean time between false alarms, ranging from 20 to 100 hours, at sampling frequencies of 5 hz, 2 hz, 1 hz and 0.2 hz. With proper choices of error bounds for the sensors, fair agreements between the actual and desired rates of false alarms were observed under normal operations. The alarm rates were found to increase (decrease) with smaller (larger) values of error bounds. The reason for this phenomenon is that the sensor noise statistics are intermediate between uniform and Gaussian. If the noise associated with each sensor was perfectly Gaussian, the alarm rates should have been independent of the error bounds.

During the tenure of the tests for several months, there were practically no unexpected false alarms. A natural failure occurred in the hardware of one of the flow sensors. Since the failure was abrupt and of large magnitude, it was immediately isolated, and the flow estimate was obtained from the remaining three sensors. To verify the fault diagnostics capability of the methodology, different types of sensor failures in excess of the error bounds were simulated while the reactor was in operation (with prior permission from the reactor safety committee). Typical cases are reported below.

(1) Faulty Sensor Calibration: Scale factor for one of the three ΔT sensors increased on-line such that the resulting offset exceeded its error bound by a modest amount. An inconsistency of this sensor with respect to the remaining sensors (that were mutually consistent) caused the isolation of the affected sensor as "high fail" within a few samples. Similar tests were successfully conducted with the power and flow sensors.

(2) Gradual Drift: Drifts were introduced in the form of ramp functions in individual measurements. Appropriate alarms were received when the drifts exceeded the respective error bounds. On the average, delays in detection decreased with increased drift rates.

To demonstrate the effect of a common-mode sensor failure, an identical drift was induced as a bias in two power sensors. Consequently, a failure was detected as this pair gradually became inconsistent with

Table I. Expected Values and Covariance Matrices

(a) Power Sensors (MW)

#1	#2	#3	#4
4.90	4.90	4.90	4.90
8.7×10^{-4}	3.9×10^{-4}	4.9×10^{-4}	5.4×10^{-4}
	7.2×10^{-4}	3.2×10^{-4}	3.8×10^{-4}
		1.17×10^{-3}	4.8×10^{-4}
			8.3×10^{-4}

(b) Primary Coolant Flow Sensors (kg/s)

#1	#2	#3	#4
143.	143.	143.	143.
1.0	0.11	0.05	0.05
	0.32	0.03	0.03
		0.35	-0.04
			0.45

(c) Temperature Difference Sensors (°C)

#1	#2	#3
8.65	8.65	8.65
1.28×10^{-2}	2.92×10^{-3}	2.30×10^{-3}
	5.03×10^{-2}	3.62×10^{-3}
		5.04×10^{-2}

the remaining pair of mutually consistent sensors. The implication is that one of the two pairs was faulty, possibly due to a common cause. An inspection of all sensor readings in this case revealed a common-mode failure of the specific sensors.

(3) Degraded Instrumentation: Random noises with zero means were added to several measurements. Alarm rates increased with larger noise to signal ratio.

(4) Failed Sensors: Sensors were disconnected one at a time from the data acquisition system, resulting in immediate isolation of the affected sensor.

(5) Abnormal Plant Operation: As a means of extracting radiation for experiments, the MITR-II contains a port through the D_2O reflector. When this port is opened, due to changes in neutron flux distribution, the scale factor for one of the flux detectors is significantly altered, thus causing an alarm for faults. In this case, an estimate of neutron power is obtained as a weighted average of the remaining sensor outputs. The operator is thus alerted to the possibility that the port may have inadvertently been opened.

Conclusions

This paper presents the application of an on-line sequential test procedure for fault diagnostics of sensor signals in an experimental fission reactor. Features of the reactor instrumentation are similar to those found in commercial power reactors, i.e., standard flow, temperature and neutron flux sensors with their attendant noise and statistical characteristics.

The concepts of the parity space and sequential probability ratio test (SPRT) are the essence of the algorithm. The methodology is suitable for on-line fault diagnostics in commercial-scale nuclear and fossil power plants as well as in chemical and process industries.

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Appendix

A.1 Fault Detection and Isolation Technique

The underlying principle of the fault detection and isolation (FDI) technique[5] is briefly described in this section. The redundant measurements for a scalar process variable such as reactor power can be modelled as

$$\underline{m} = Hx + \underline{\varepsilon} \qquad \text{(A-1)}$$

where $\underline{m}$ is the (ℓx1) array of measurements for the process variable whose true value is x. The array $\underline{\varepsilon}$ represents measurement noise such that, for normal functioning of each measurement, $|\varepsilon_i| \leq b_i$, the specified error bound with $i = 1,2,\ldots,\ell$. For scalar sensors, the measurement matrix can be chosen as $H = [1\ 1\ \cdots\ 1]^T$ without loss of generality. Any two measurements at the sampling instant n are consistent if they differ by no more than the sum of the allowable errors for each of them.

$$|m_i(n) - m_j(n)| \leq b_i(n) + b_j(n) , \quad i = 1,2,\ldots,\ell \quad j = 1,2,\ldots,\ell \qquad \text{(A-2)}$$

The consistency of each pair of measurements can be determined solely on the basis of current observations as defined above or by sequential tests, described in Section A.2, that rely on past observations as well. As occasional inconsistencies are likely to occur when no failures are present, sequential tests are useful in reducing the probability of false alarms.

Since the consistencies among all pairs of measurements is independent of x, the true value of the process variable, the measurement vector $\underline{m}$ is projected onto the left null space of the measurement matrix, called the parity space,[6] such that the variations in the underlying variable x are eliminated and only the effects of the noise vector $\underline{\varepsilon}$ are observed. The projection of $\underline{m}$ onto the parity space of dimension (ℓ-1), known as the parity vector, is given as

$$\underline{p} = V\underline{m} = V\underline{\varepsilon} \quad \text{(A-3)}$$

where V is chosen such that its (ℓ-1) rows form an orthonormal basis for the parity space, i.e.,

$$VH = 0 , \quad VV^T = I_{\ell-1},$$

$$\text{and} \quad V^TV = I_\ell - H(H^TH)^{-1}H^T \quad \text{(A-4)}$$

For normal operations, when no measurements have failed, the parity vector $\underline{p}$ is small, reflecting acceptable errors in all measurements which are mutually consistent within the allowable error bounds. If a failure occurs, the parity vector grows in magnitude in the direction(s) associated with the failed measurement(s). An increase in the magnitude of the parity vector signifies detection of a failure, and its relative orientation with respect to the failure directions can be used to identify the failed measurement(s). Reference 5 provides a systematic approach to fault detection and isolation in a set of ℓ measurements by concurrently checking the consistencies of all $\ell(\ell-1)/2$ pairs of measurements in terms of their error bounds. For example, consider three measurements m_1, m_2, and m_3 for a process variable. If one of the measurements, say m_1, is faulty, then only one pair, namely (m_2, m_3), will exhibit consistency, and consequently the measurement m_1 will be isolated. An estimate $\hat{x}$ of the measured variable can be evaluated as a weighted average of the consistent measurements m_2 and m_3. However, absence of any consistent pair signifies failure of at least two out of the three measurements where a fault can be detected but not isolated; in that case it may not be possible to obtain an estimate $\hat{x}$. A geometric interpretation of this methodology, along with further details, is given in Reference 5.

A.2 Development of the Sequential Test Algorithm

The difference between two measurements in the kth pair (see equation (A-2)) at the sampling instant n is defined as

$$\xi_k(n) = m_i(n) - m_j(n) , \quad \begin{array}{l} i = 1,2,\ldots,\ell \\ j = 1,2,\ldots,\ell \\ k = 1,2,\ldots,\ell(\ell-1)/2 \end{array} \quad \text{(A-5)}$$

Assuming that the measurement noise $\underline{\varepsilon}$ is stationary, the stochastic variables $\xi_k(n)$ are normalized as

$$\gamma_k(n) = \xi_k(n) / \sigma_k \quad \text{(A-6)}$$

where σ_k is obtained from the variances and cross-covariance of m_i and m_j (see Table I). Thus, at every sampling instant n, $E(\gamma_k(n)) = 0$ and $\mathrm{Var}(\gamma_k(n)) = 1$ for $k = 1,2,\ldots,\ell(\ell-1)/2$. The noise distribution of γ_k is assumed Gaussian on the justification that γ_k is a linear combination of m_i and m_j whose noise statistics were found (by experimentation) to be intermediate between uniform and Gaussian.

In the sequential tests, a decision is made between H_0, the no-failure hypothesis, and H_1, the failure hypothesis, on the basis of the information processed at consecutive samples. The hypotheses H_0 and H_1 are defined as

H_0: The process $\gamma_k(n)$ at the sampling instant n is Gaussian with zero mean and unit variance.

H_1: The process $\gamma_k(n)$ at the sampling instant n is Gaussian with mean $\pm\mu_k(n)$ and unit variance.

The mean in the failure hypothesis H_1 can be positive or negative signifying high or low failures, respectively.

The log likelihood ratio at the jth sample is defined as

$$\zeta_k(j) = -\ell n \frac{p(\gamma_k(j)|H_1)}{p(\gamma_k(j)|H_0)} , \quad k = 1,2,\ldots,\ell(\ell-1)/2 \quad \text{(A-7)}$$

Then, the log likelihood ratio $\lambda_k(n)$ for n consecutive (conditionally) independent samples is given by

$$\lambda_k(n) = -\ell n \frac{p(\gamma_k(1), \gamma_k(2), \cdots, \gamma_k(n)|H_1)}{p(\gamma_k(1), \gamma_k(2), \cdots, \gamma_k(n)|H_0)} = \sum_{j=1}^{n} \zeta_k(j) \quad \text{(A-8)}$$

which yields the following recursive relations for positive (μ_k) and negative ($-\mu_k$) values of the mean in hypothesis H_1:

$$\begin{aligned} \lambda_k^+(n) &= \lambda_k^+(n-1) + \mu_k(n)(\mu_k(n)/2 - \gamma_k(n)) \\ \lambda_k^-(n) &= \lambda_k^-(n-1) + \mu_k(n)(\mu_k(n)/2 + \gamma_k(n)) \end{aligned} \quad \text{(A-9)}$$

Following Chien's sequential test procedure,[3] the algorithm is formulated as follows:

- Initialization:

  $\lambda_k^+(0) = \lambda_k^-(0) = 0 , \quad k = 1,2,\ldots,\ell(\ell-1)/2$

- Lower limit setting:

  $\lambda_k^+(n) = \mathrm{Max}\,[\lambda_k^+(n), 0]$, $\lambda_k^-(n) = \mathrm{Max}\,[\lambda_k^-(n), 0]$ for all $n > 0$

- Consistency of kth pair:

  $\lambda_k^+(n) < \theta_k(n)$ and $\lambda_k^-(n) < \theta_k(n)$ for all $n > 0$

- Inconsistency of kth pair:

$$\lambda_k^+(n) \geq \theta_k(n) \text{ or } \lambda_k^-(n) \geq \theta_k(n) \text{ for all } n > 0$$

- Upper limit setting:

$$\lambda_k^+(n) = \text{Min}\,[\lambda_k^+(n),\ \phi_k(n)] \quad \text{for all } n > 0$$
$$\lambda_k^-(n) = \text{Min}\,[\lambda_k^-(n),\ \phi_k(n)]$$

where $\theta_k(n) = \ln[N(\mu_k(n))^2/2)]$ is the detection threshold, N being the mean time, i.e., the number of samples, between false alarms (N>>1), and the parameter $\phi_k(n)$ [greater than or equal to $\theta_k(n)$], for upper limit setting, allows possible self-recovery of temporarily degraded sensors that are not failed by the FDI technique of Section A.1. The recovery takes longer with larger values of ϕ_k. In this study, $\phi_k(n)$ was selected to be equal to $\theta_k(n)$. The lower limit of λ's is set to include the effects of a priori probabilities of sensor failures between consecutive samples.[3]

The magnitude μ_k of the mean can be chosen as a function of the error bounds (of the appropriate pair of measurements) that can be specified on the basis of instrument manufacturer's specifications or the actual measurement noise statistics. For example, μ_k can be modelled, in view of the equations (A-2), (A-6) and (A-9), as

$$\mu_k(n) = 2\chi\,[b_i(n) + b_j(n)] / \sigma_k \qquad \text{(A-10)}$$

where the parameter χ is chosen in the vicinity of 1. Furthermore, if the error bounds are time-independent, then the means $\mu_k(n) = \mu_k$ at all sampling instants.

The information on consistencies and inconsistencies of all measurement pairs, obtained from the sequential tests, is applied in the FDI technique of Section A.1.

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