NUCLEAR PLANT COMPONENT SURVEILLANCE IMPLEMENTED IN SAS® SOFTWARE

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ABSTRACT

It has become common practice in nuclear power plants to install redundant sensors for monitoring critical physical variables (pressures, temperatures, radiation levels, etc.). This paper reports on the design and testing of an extremely sensitive component-operability surveillance algorithm that is based on the sequential probability ratio test (SPRT). The SPRT technique, implemented in SAS® software, processes the stochastic components of digitized signals from identical sensors on two or more components in an operating reactor for detection and annunciation of off-normal operation. Information made available from the SPRT can provide a reactor operator with early identification of the incipient or onset of conditions that could lead to plant operational degradation, thereby enabling him or her to terminate or avoid events which might challenge safety or radiological performance guidelines. At the same time, the SPRT enhances plant availability and economics by minimizing unnecessary reactor trips caused in conventional systems by occasional spurious data values that might exceed a simple high/low limit check. An example application of the SPRT for surveillance of primary coolant pump operability in the Experimental Breeder Reactor-II is presented.

INTRODUCTION

Experimental Breeder Reactor No. II (EBR-II) is a liquid-metal-cooled reactor (LMR) operated for the U.S. Department of Energy by Argonne National Laboratory near Idaho Falls, Idaho. It is currently the only operating electrical-power-producing LMR in the U.S. The primary mission of the EBR-II plant is to serve as a test bed and proving ground for future LMR technology and innovations. The plant is well-instrumented with temperature, pressure, flow, radiation, and other sensors, particularly along its three principal heat transport circuits. As is the practice in all U.S. nuclear reactors, multiple redundant sensors are installed for monitoring all physical parameters having any safety significance.

The goal of the present paper is to present the adaptation of an extremely sensitive statistical test, the sequential probability ratio test (SPRT) [1], for surveillance of signals from identical sensors deployed for redundant readings of continuous physical processes. If any disturbance causes the noise characteristics for one monitored signal to change (e.g., a large variance, skewness, or signal bias) then the SPRT provides a rapid annunciation of that disturbance. An example of the use of the SPRT for surveillance of primary coolant pump operability is presented using data recorded during a pump disturbance event that occurred during full-power operation in EBR-II.

SAS software was chosen for this project because of the language's powerful coding features and its ability to model prototype systems quickly and cost-effectively. All experimental data employed in this investigation were first tested for non-Gaussian effects using the Kolmogorov-Smirnov test with PROC SPECTRA. SAS macro language was exploited in a parametric sensitivity study to explore the effects of small changes in variance and bias on the expected number of observations needed for annunciation of discrepant signals using the SPRT. Finally, PROC 630 proved indispensable for displaying results of our many-variable sensitivity investigation.

THEORETICAL DEVELOPMENT

Our objective is to analyze successive observations of a discrete process \( Y \), which represents a comparison of the stochastic components of two physical processes monitored by similar sensors. Let \( y_k \) represent a sample from the process \( Y \) at time \( t_k \). During normal operation with an undegraded physical system and with sensors that are functioning within specifications the \( y_k \) should be normally distributed with mean \( \mu \). Note that if the two signals being compared do not have the same nominal means (due, for example, to differences in calibration) then the input signals will be pre-normalized to the same nominal mean values during initial operation.

Our specific goal is to declare system 1 or system 2 degraded if the drift in \( Y \) is sufficiently large that the sequence of observations appears to be distributed about mean \( +M \) or \( -M \), where \( M \) is our pre-assigned system-disturbance magnitude.

The SPRT provides a quantitative framework that enables us to decide between two hypotheses, namely,

\[ H_0: \ Y \text{ is drawn from a Gaussian PDF with mean } \mu \text{ and variance } \sigma^2. \]
H₂: Y is drawn from a Gaussian PDF with mean 0 and variance s².

We will suppose that if H₁ or H₂ is true, we wish to decide for H₁ or H₂ with probability (1 - α) or (1 - a), respectively, where α and a represent the error (misidentification) probabilities.

From the theory of Wald [2], our most powerful test depends on the likelihood ratio Lₙ, where

\[ Lₙ = \frac{\text{Prob of observed sequence } Y₁, Y₂, \ldots, Yₙ, \text{ given } H₁ \text{ true}}{\text{Prob of observed sequence } Y₁, Y₂, \ldots, Yₙ, \text{ given } H₂ \text{ true}} \]  

After n observations have been made, the sequential probability ratio is just the product of the probability ratios for each step:

\[ Lₙ = (PR₁) \cdot (PR₂) \cdot \ldots \cdot (PRₙ) \]  

or

\[ Lₙ = \frac{f(y₁ | H₁)}{f(y₁ | H₂)} \frac{f(y₂ | H₁)}{f(y₂ | H₂)} \cdots \frac{f(yₙ | H₁)}{f(yₙ | H₂)} \]  

where \( f(y | H) \) is the distribution of the random variable y.

Wald’s theory operates as follows: Continue sampling as long as

\[ A < Lₙ < B \]  

Stop sampling and decide H₁ as soon as \( Lₙ > B \), and stop sampling and decide H₂ as soon as \( Lₙ < A \). The acceptance thresholds are related to the error (misidentification) probabilities by the following expressions:

\[ A = \frac{β}{1 - α}, \quad B = \frac{1 - β}{α} \]  

α is the probability of accepting H₁ when H₂ is true.

β is the probability of accepting H₂ when H₁ is true.

If we can assume that the random variable \( Y_k \) is normally distributed, then the likelihood that H₁ is true (i.e., mean M, variance s²) is given by:

\[ L(y₁, y₂, \ldots, yₙ | H₁) = \frac{1}{(2πn)^{n/2} s^n} \exp \left[ -\frac{1}{2s^2} \left( \sum_{k=1}^{n} y_k^2 - 2 \sum_{k=1}^{n} y_k M + \sum_{k=1}^{n} M^2 \right) \right] \]  

Similarly for H₂ (mean 0, variance s²):

\[ L(y₁, y₂, \ldots, yₙ | H₂) = \frac{1}{(2πn)^{n/2} s^n} \exp \left[ -\frac{1}{2s^2} \left( \sum_{k=1}^{n} y_k^2 \right) \right] \]  

The ratio of (6) and (7) gives the likelihood ratio \( Lₙ \)

\[ Lₙ = \exp \left[ -\frac{1}{2s^2} \sum_{k=1}^{n} M(y_k - M)^2 \right] \]  

Combining (4), (5), and (8), and taking natural logs gives

\[ \ln \frac{β}{1 - α} < -\frac{1}{2s^2} \sum_{k=1}^{n} M(y_k - M)^2 < \ln \frac{1 - \alpha}{α} \]  

Define SPRT:

\[ \frac{1}{2s^2} \sum_{k=1}^{n} M(y_k - M)^2 \]  

then

\[ \text{SPRT} < \ln \frac{β}{1 - α} \quad \text{Accept } H₂ \]  

\[ \text{SPRT} < \ln \frac{1 - \alpha}{α} \quad \text{Continue Sampling} \]  

\[ \text{SPRT} < \ln \frac{β}{1 - α} \quad \text{Accepts } H₁ \]  

Following Wald’s sequential analysis, it has been shown [3] that a decision test based on the SPRT has an optimal property; that is, for given probabilities α and β there is no other procedure with at least as low error probabilities or expected risk and with shorter length average sampling time than the SPRT. It is because of this property of the SPRT and because of its inherent simplicity as shown in (11) that the SPRT was chosen as the disturbance-annunciation tool for this project.

Note that the SPRT formulated here cannot be applied directly to non-Gaussian signals. All of the experimental data employed in the pump-surveillance application presented below were tested for departure from normality using the Kolmogorov-Smirnov test via the WHITETEST option of PROC SPECTRA. For applications to nuclear-system signals contaminated by non-Gaussian noise, an attempt must first be made to pretreat the input signals with a normalizing transformation (often as simple as subtracting out a bias). SPRTs can be formulated for applications to non-Gaussian signals, but the analytical complexity becomes far greater.
PARAMETRIC STUDY OF SPRT SENSITIVITY
AND RESPONSE TIME

A detailed parametric sensitivity study has been performed using recursive execution of SAS macros on CMS SAS. The objective of this portion of our investigation was to systematically explore the effects of variations on SPRT parameters on the overall sensitivity and response time. PROC COD proved very useful for this stage of our investigation.

Figure 1 illustrates the effect of varying the error probabilities α and β. For any given value α and β (horizontal coordinate plane) the corresponding point on the 3-D surface represents the acceptance threshold A (see Eqn. 5) for deciding hypothesis H2. The surface depicted in Fig. 2 illustrates the influence of variations in α and β on the value of the upper acceptance threshold, B.

To assess the average sampling time that will be required to annunciate a failure with the SPRT technique, calculations were made of the average number of samples required to reach the positive threshold, B, under various levels of signal degradation. The expected sampling time is a function of the signal variance, V (defined by \( V = \sigma^2 \)), the assigned failure magnitude, M, and the postulated mean of the difference function Y. Example contour plots generated during this portion of our investigation are illustrated in Figs. 3 and 4. Figure 3 shows a family of constant-variance contours with mean(Y) increasing. The effect of increasing signal variance, V, for given values of mean(Y) is illustrated in Fig. 4.

EXAMPLE APPLICATION USING REACTOR PLANT DATA

To illustrate an application of the SPRT for primary pump operability surveillance, archive data were retrieved from an actual pump-degradation event that occurred in EBR-II in March, 1987. Figure 5 plots several pump parameters that were recorded during the event. The upper subplot in Fig. 5 shows the power, expressed in KW, required to operate the two coolant pumps in EBR-II. The second subplot shows the pump-shaft rotation speed. The third subplot plots the ratio of pump speed to power for both pumps, which gives a qualitative measure of the pump operating efficiency. All data shown were recorded at 5-s intervals. Note that at about T=6 min there is a discernable increase in pump KW for pump 1. This is an indication of a shaft-binding problem, manifested by an increase in rotating friction. At about T=10 min the KW reached its limit for pump 1 and the total coolant flow rate began to fall off. This caused an increase in pump 2 KW, until that pump also reached its maximum limit. At T=15.3 min the coolant flow dropped sufficiently to trigger an automatic scram (rapid shutdown) of the reactor. Figure 6, which plots the same data against an expanded time scale, shows that the speed/power ratio started to drop at about T=7 min.

Figure 7 shows the results of applying the SPRT technique to the data recorded during the binding event. Pump power signals were used as input to the SPRT algorithm. The difference function Y, plotted in the third subplot in Fig. 7 represents the difference between pump 1 and pump 2 powers, after normalizing the power to a common nominal value.

The bottom subplot in Fig. 7 shows the computed value of the SPRT index. The significance of the SPRT index is: If the statistical quality of either pump power signal begins to change, which may result from sensor degradation or from a disturbance in the physical process being monitored, then the SPRT index is driven positive at a rate that increases with the degree of degradation. If the index reaches a threshold value of 0.6, then one can conclude with a confidence factor of 99% that the two signals are no longer governed by the same PDF. At this point the status of a warning flag is set, the SPRT index is reset to zero, and the calculations continue.

From the lower plot in Fig. 4 it can be seen that by the time pump 1 power started increasing, the SPRT was continuously exceeding the positive threshold (diamond symbols at 4.60). The interesting feature that emerges from the plot is that several minutes before there was a discernible increase in pump power, the SPRT was indicating "data-disturbance" warnings. It can be concluded that at the time the data recording was initiated, the statistical quality of the pump 1 parameter was already significantly different (at the 99% confidence level) than pump 2.

CONCLUSIONS

The sequential probability ratio test, adapted from the theory of Wald, has been chosen as a disturbance annunciation tool for signal validation and for monitoring component operability in nuclear power reactors. The SAS-system macros developed for the pump operability surveillance system presented here are quite general and may be applied in a wide variety of applications wherein identical sensors are deployed for redundant readings of continuous physical processes.
REFERENCES


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Investigation of SPRT Sensitivity for Early Annunciation of Pump Degradation