Conf-920538--25

Summary of full paper to be presented at the 8th Power Plant Dynamics, Control & Testing Symposium, May 27-29, 1992, Knoxville, Tennessee

ANL/CP--75528

DE92 014771

Spectrum-Transformed Sequential Testing Method for Signal Validation Applications

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Work supported by the U. S. Department of Energy, Nuclear Energy Programs under Contract W-31-109-Eng-38.

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ABSTRACT

The Sequential Probability Ratio Test (SPRT) has proven to be a valuable tool in a variety of reactor applications for signal validation and for sensor and equipment operability surveillance. One drawback of the conventional SPRT method is that its domain of application is limited to signals that are contaminated by gaussian white noise. Nongaussian process variables contaminated by serial correlation can produce higher-than-specified rates of false alarms and missed alarms for SPRT-based surveillance systems. To overcome this difficulty we present here the development and computer implementation of a new technique, the spectrum-transformed sequential testing method. This method retains the excellent surveillance advantage of the SPRT (extremely high sensitivity for very early annunciation of the onset of disturbances in monitored signals), and its false-alarm and missed-alarm probabilities are unaffected by the presence of serial correlation in the data. Example applications of the new method to serially-correlated reactor variables are demonstrated using data recorded from EBR-II.

Introduction

In recent years the Sequential Probability Ratio Test (SPRT) [Refs. 1-4] has found wide applications as a signal validation tool in the reactor industry. Two features of the SPRT that make it attractive for parameter surveillance and fault detection are (1) very early annunciation of the onset of a disturbance in noisy process variables, and (2) the fact that the SPRT has user-specifiable false-alarm and missed-alarm probabilities. One drawback of the SPRT that has limited its adaptation to a broader range of nuclear plant applications is the fact that its mathematical formalism is founded upon an assumption that the signals it is monitoring are purely gaussian, independent (white noise) random variables. We have undertaken a detailed statistical analysis of a wide variety of plant signals at ANL's Experimental Breeder Reactor-II (EBR-II). Our findings show that many types of variables throughout the primary and secondary systems of EBR-II are contaminated by noise that is serially correlated. We have found that the presence of serial correlation in a process variable monitored by a SPRT module can lead to excessive false-alarm and/or missed-alarm probabilities.

To avoid these difficulties, and to expand the domain of automated signal-validation methods, we introduce here a new technique for signal validation and for sensor and equipment operability surveillance applications. The technique is called the Spectrum-Transformed Sequential Testing (STST, or ST2) method. We call the ST2 method a dual transformation method, insofar as it entails both a frequency-domain transformation of the original time-series data and a subsequent time-domain transformation of the resu'tant spectrally-filtered data.

For a stationary time series $\mathbf{Y}_t$, the approach is to first perform a frequency-domain transformation of the original $\mathbf{Y}_t$ by a simple Fourier series expansion:

$$\mathbf{Y}_t = \frac{\mathbf{a}_0}{2} + \sum_{m=1}^{N/2} \left[\mathbf{a}_m \cos(\omega_m \mathbf{t}) + \mathbf{b}_m \sin(\omega_m \mathbf{t})\right] \tag{1}$$

where $\mathbf{a}_0/2$ is the mean value of the series, $\mathbf{a}_m$ and $\mathbf{b}_m$ are the Fourier coefficients corresponding to the Fourier frequency ω_m, and N is the total number of observations. Using the Fourier coefficients, we next generate a composite function, $\mathbf{X}_t$, using the values of the largest harmonics identified in the Fourier transformation of $\mathbf{Y}_t$. The following numerical approximation to the Fourier transform is useful in determining the Fourier coefficients $\mathbf{a}_m$ and $\mathbf{b}_m$. Let $\mathbf{x}_j$ be the value of $\mathbf{X}_t$ at the jth time incrcment. Then assuming 2π periodicity and letting $\omega_m = 2\pi\mathbf{m}/\mathbf{N}$, the approximation to the Fourier transform yields:

$$\mathbf{a}_m = \frac{2}{N} \sum_{j=0}^{N-1} \mathbf{x}_j \cos(\omega_m \mathbf{j}) \qquad \mathbf{b}_m = \frac{2}{N} \sum_{j=0}^{N-1} \mathbf{x}_j \sin(\omega_m \mathbf{j}) \tag{2}$$

for $0<\mathbf{m}<N/2$. Finally, the power spectral density (PSD) function for the signal is given by $\mathbf{l}_m$, where

$$\mathbf{l}_m = N \frac{\mathbf{a}_m^2 + \mathbf{b}_m^2}{2} \tag{3}$$

In our investigations with EBR-II signals, the highest eight $\mathbf{l}_m$ modes were found to give an accurate reconstruction of $\mathbf{X}_t$ while reducing most of the serial correlation for the physical variables we have studied. (Nevertheless, the number of modes is left as a user-supplied input variable in our ST2 surveillance software to facilitate extension to new system applications.)

The generation of the Fourier composite $\mathbf{X}_t$ uses the general form of Eqn. (1), where the coefficients and frequencies employed are those associated with the eight highest PSD amplitudes. This yields a composite curve with essentially the same correlation structure and exactly the same mean as $\mathbf{Y}_t$. Finally, we generate a discrete residual function $\mathbf{R}_t$ by differencing corresponding values of $\mathbf{Y}_t$ and $\mathbf{X}_t$. This residual function, which is devoid of serially correlated contamination, is then processed with the SPRT binary-hypothesis test developed in detail in Ref. 1.

EXAMPLE APPLICATIONS TO MEASURED PLANT SIGNALS

We have selected variables from EBR-II's reactor coolant pumps (RCPs) and delayed neutron (DN) monitoring systems to demonstrate the power and utility of the ST2 algorithm. The RCP and DN systems were chosen for initial application of the ST2 approach because SPRT-based expert system tools have already been under development for both [1,5,6]. All data used in this investigation were recorded during full-power, steady state operation at EBR-II. The data have been digitized at a 2-per-second sampling rate using 2^{14} (16,384) observations for each signal of interest.

Figure 1 demonstrates the spectral filtering approach as applied to EBR-II's primary pump 1 power signal, which measures the power (in kW) needed to operate RCP 1. The first subplot in the figure shows 136 minutes of the original signal as it was digitized at the 2-Hz sampling rate. The second subplot shows a Fourier composite constructed from the eight most prominent harmonics identified in the original signal. The residual function, obtained by subtracting the Fourier composite curve from the raw data, is shown in subplot 3. Periodograms of the raw signal and the residual function have been computed and are plotted in Fig. 2. Note the presence of eight depressions in the periodogram of the residual function corresponding to the most prominent periodicities in the original, unfiltered data. Histograms computed from the raw signal and the residual function are plotted in Fig. 3. For each histogram shown we have superimposed a gaussian curve (solid line) computed from a purely gaussian distribution having the same mean and variance. Comparison of the two subplots in Fig. 3 provides an *ad ocular* demonstration of the effectiveness of spectral filtering in reducing asymmetry in the histogram of the spectrally filtered versus the original time series. Quantitatively, this decreased asymmetry is reflected in a decrease in the skewness (or third moment of the noise) from 0.15 (raw signal) to 0.10 (residual function).

It should be noted here that selective spectral filtering, which we have designed to reduce the consequences of serial correlation in our sequential testing scheme, does not guarantee that the degree on non-normality in the data will also be reduced. Fortuitously, for 80% of the signals we have investigated at EBR-II, the reduction in serial correlation is accompanied by a reduction in the absolute value of the skewness for the residual function. Moreover, in the cases where there is not a reduction in skewness, it can generally be observed that the skewness is very small to begin with. Finally, it has been shown in a separate investigation [7] that nonnormality is much less of a problem, in terms of affecting SPRT misidentification probabilities, than is nonwhiteness.

To quantitatively evaluate the improvement in whiteness effected by the spectral filtering method we employ the Fisher Kappa white noise test [8]. For each time series we compute the Fisher Kappa statistic from the defining equation

Figure 1
Spectral Decomposition of Pump 1 Power

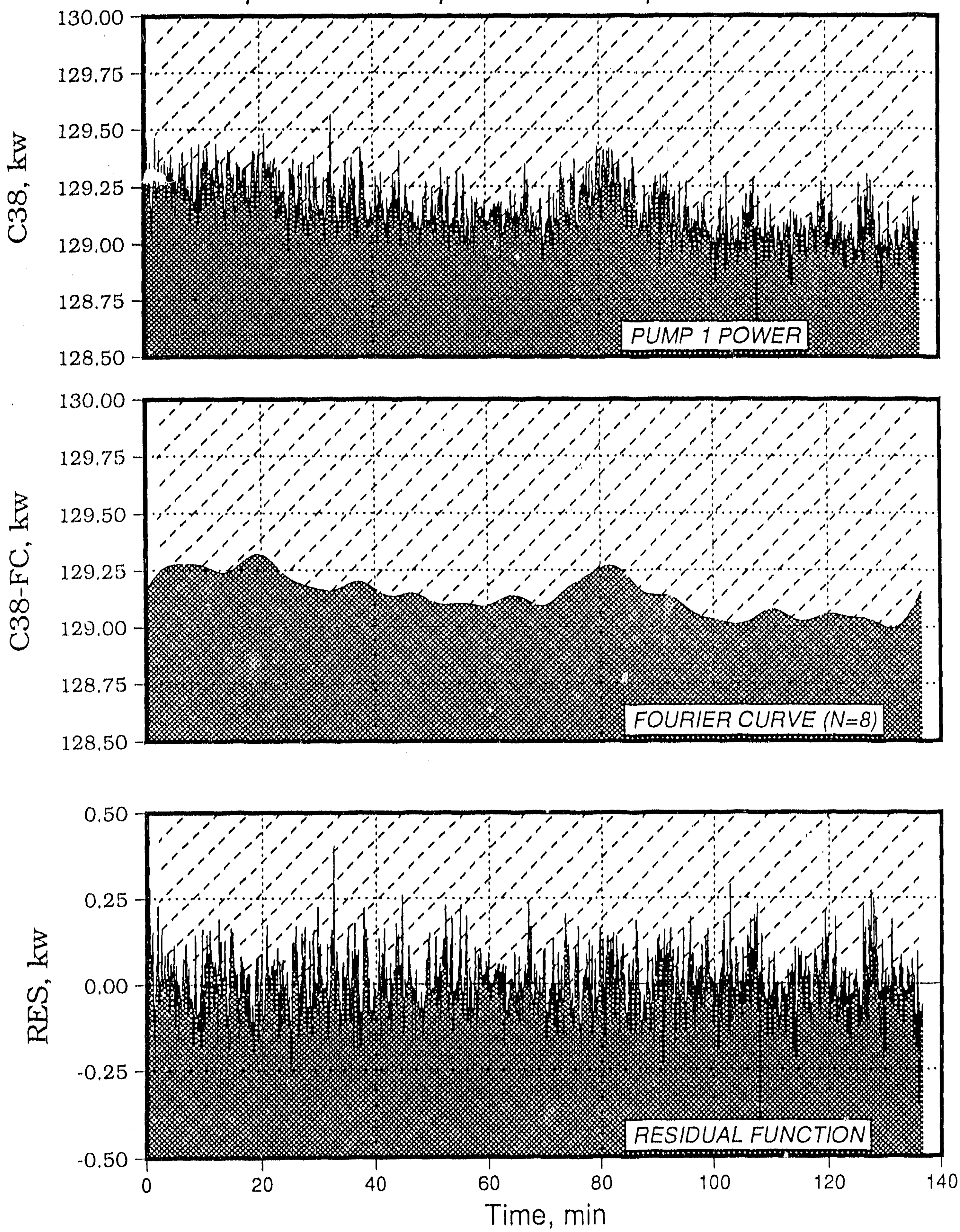


Figure 2

Power Spectral Density of Pump 1 Power

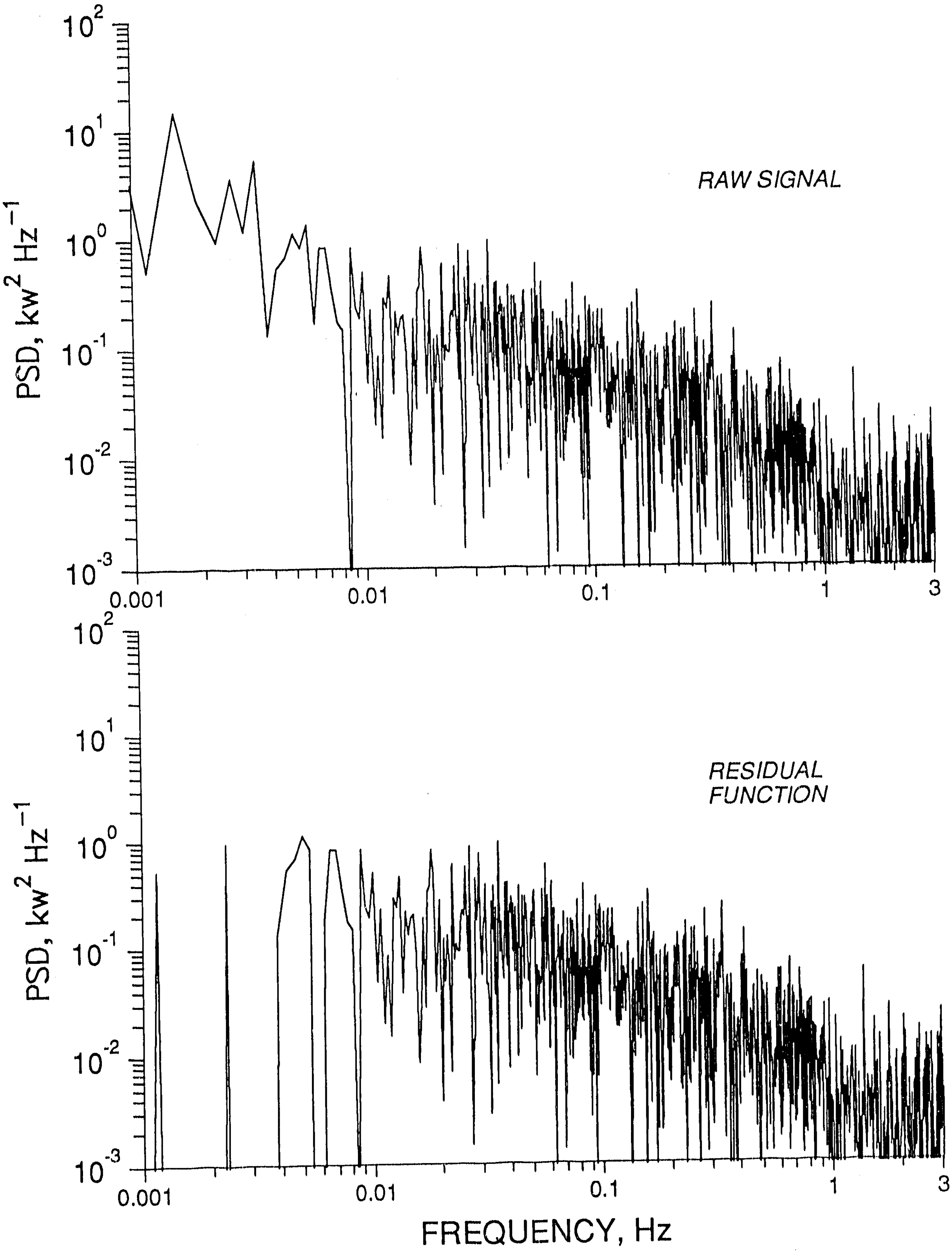
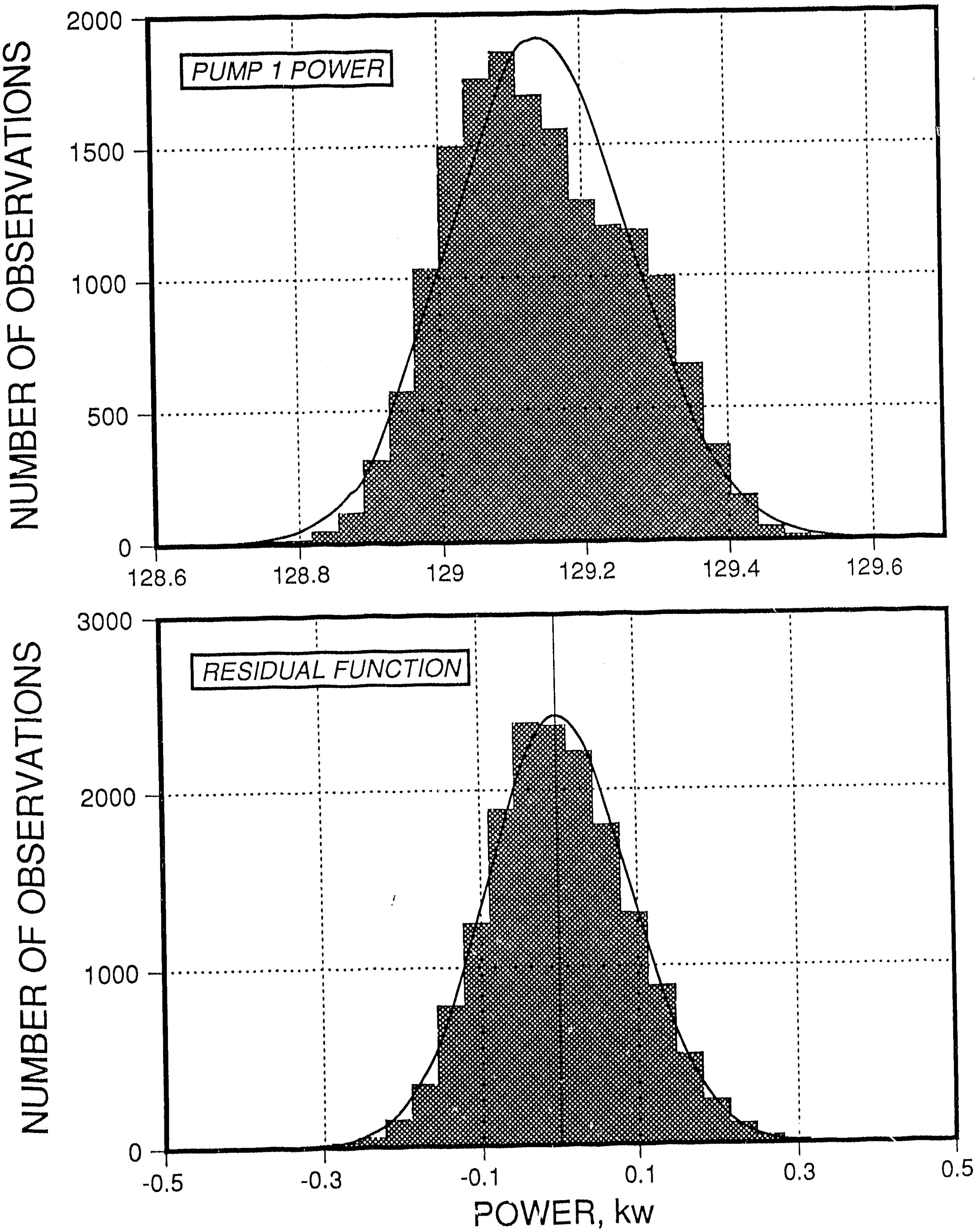


Figure 3

Noise Histograms for Pump 1 Power



$$\kappa = \left[\frac{1}{N} \sum_{k=1}^{N} I(\omega_k) \right]^{-1} I(L) \qquad (4)$$

where $I(\omega_k)$ is the PSD function (see Eq. 3) at discrete frequencies ω_k, and $I(L)$ signifies the largest PSD ordinate identified in the stationary time series.

In words, the Kappa statistic is the ratio of the largest PSD ordinate for the signal to the average ordinate for a PSD computed from a signal contaminated with pure white noise. For EBR-II's pump 1 power signal used in the present example κ is 1940 and 68.7 for the raw signal and the residual function, respectively. Thus, we can say that the spectral filtering procedure has reduced the degree of nonwhiteness in the signal by a factor of 28. Strictly speaking, the residual function is still not a pure white noise process. The 95% critical value for Kappa for a time series with 2^{14} observations is 12.6. This means that only for computed Kappa statistics lower than 12.6 could we accept the null hypothesis that the signal is contaminated by pure white noise. The fact that our residual function is not white is reasonable on a physical basis, for the complex interplay of mechanisms that influence the stochastic components of a physical process would not be expected to have a purely white correlation structure. The important point, however, is that the reduction in nonwhiteness effected by the spectral filtering procedure using only the highest eight harmonics in the raw signal has been found to preserve the pre-specified false alarm and missed alarm probabilities in the SPRT sequential testing procedure (see below). Table I summarizes the computed Fisher Kappa statistics for 13 EBR-II plant signals that are used in SPRT-based surveillance systems at ANL. In every case the table shows a substantial improvement in signal whiteness.

DEMONSTRATION OF COMPLETE ST-2 PROCEDURE

The complete ST2 algorithm integrates the spectral decomposition and filtering steps illustrated above with the SPRT binary hypothesis procedure developed in detail in Ref. 1. The general procedure is demonstrated by application of a SPRT to two redundant delayed neutron detectors (designated DND A and DND B) whose signals were archived during long-term normal (i.e. undegraded) operation with a steady DN source in EBR-II. For demonstration purposes a SPRT was designed with a false alarm rate, α, of 0.01. Although this value is higher than we would designate for a production surveillance system, it gives a reasonable frequency of false alarms so that asymptotic values of α can be obtained with only tens of thousands of discrete observations. According to the theory of the SPRT, it can be easily proved [1,4] that for purely gaussian, independently distributed processes α provides an upper bound to the probability (per observation interval) of obtaining a false alarm--i.e. obtaining a "data disturbance" annunciation when, in fact, the signals under surveillance are undegraded.

Figures 4 and 5 demonstrate sequences of SPRT results for raw DND signals and for spectrally-whitened DND signals, respectively. In each figure the first two subplots show the DN signals from detectors DND-A and DND-B, where the steady-state values of the signals have been normalized to zero.

TABLE I

Effectiveness of Spectral Filtering for Measured Plant Signals

Plant Variable I.D.	Fisher Kappa Test Statistic (N=16,384)	
	Raw Signal	Residual Function
Pump 1 Power	1940	68.7
Pump 2 Power	366	52.2
Pump 1 Speed	181	25.6
Pump 2 Speed	299	30.9
Pump 1 Radial Vibr (top)	123	67.7
Pump 2 Radial Vibr (top)	155	65.4
Pump 1 Radial Vibr (bottom)	1520	290.0
Pump 2 Radial Vibr (bottom)	1694	80.1
DN Monitor A	96	39.4
DN Monitor B	81	44.9
DN Detector 1	86	36.0
DN Detector 2	149	44.1
DN Detector 3	13	8.2

Figure 4
Investigation of SPRT Misidentification Probabilities
CASE 1: Unfiltered DN Signals from EBR-II

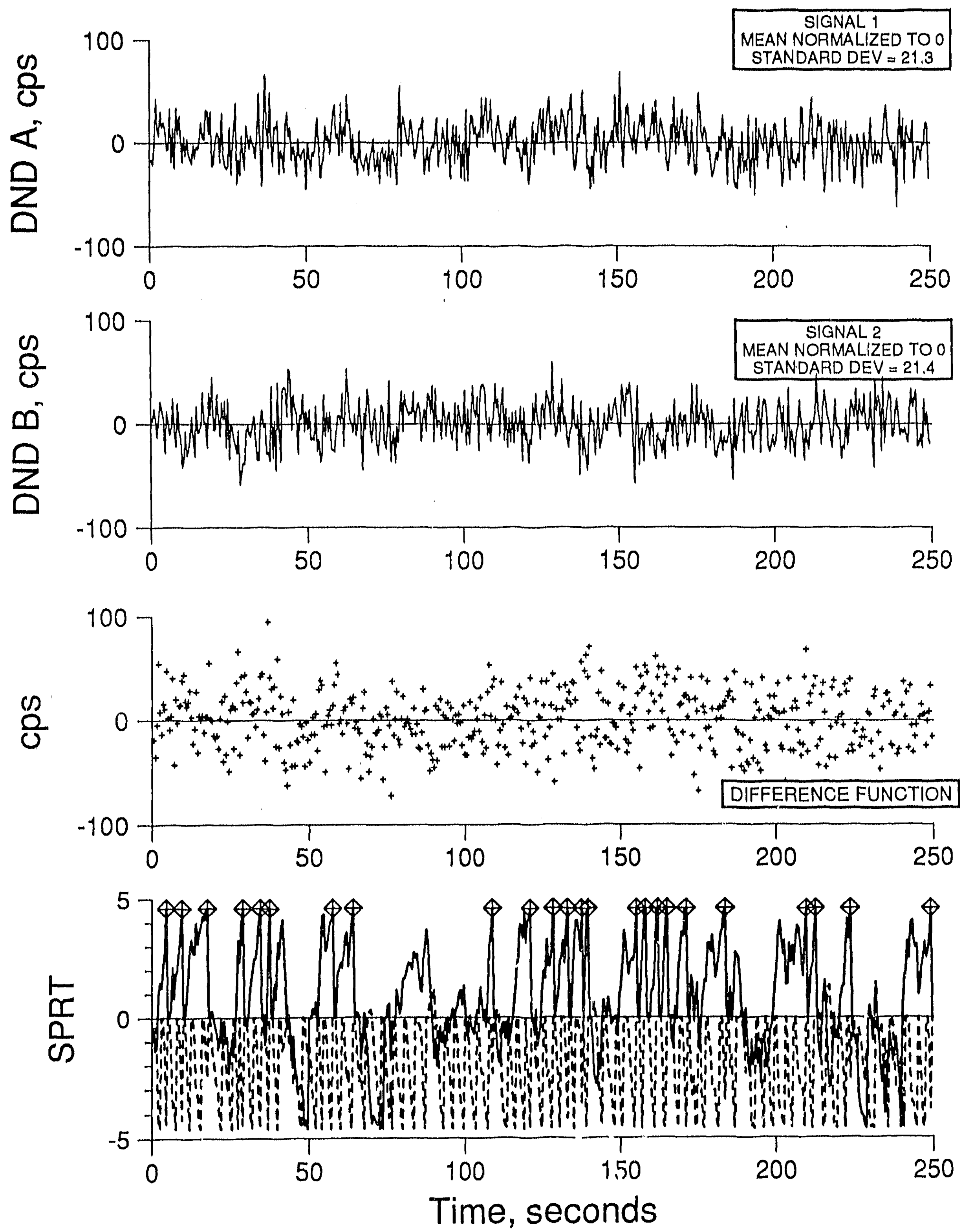
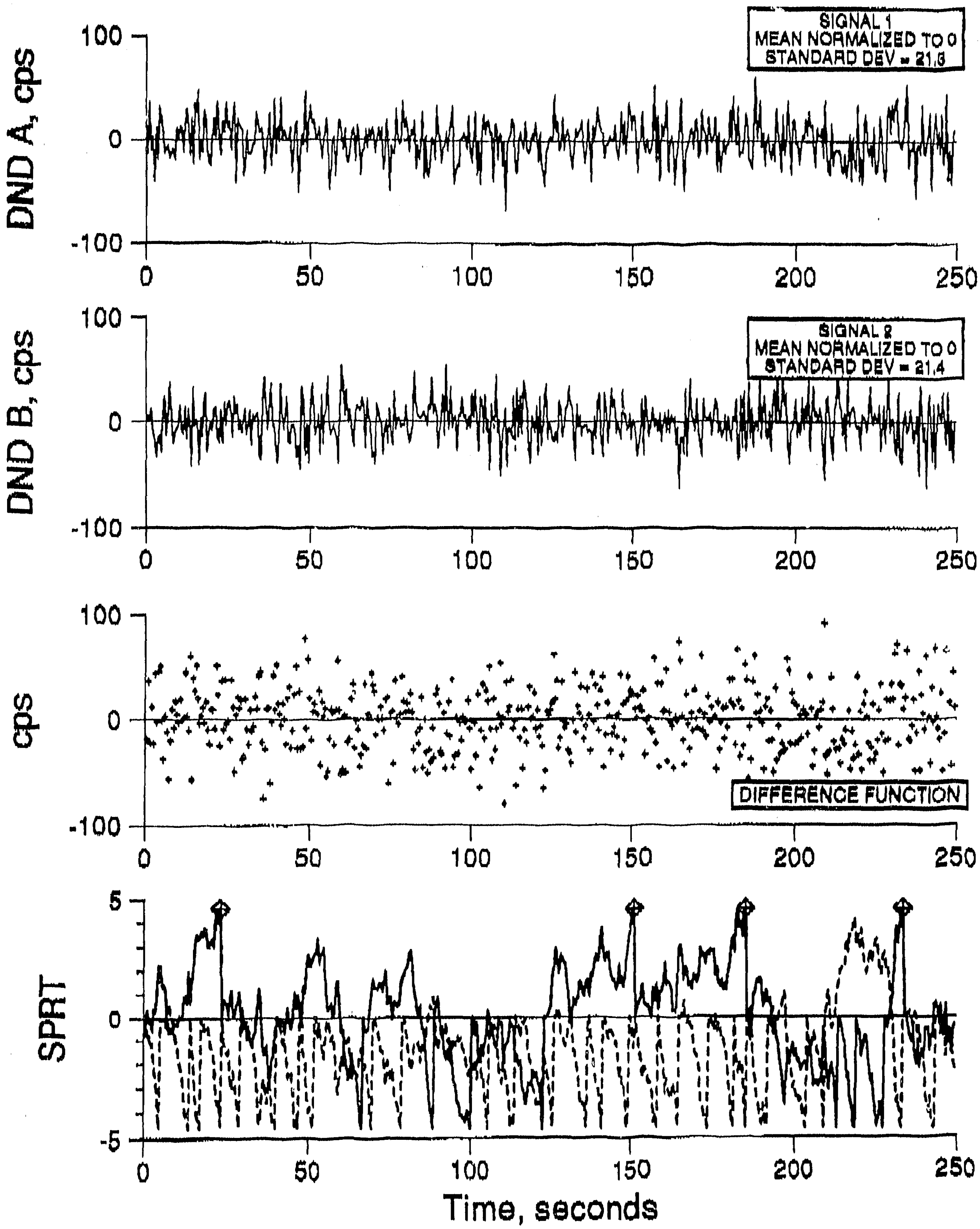


Figure 5
Investigation of SPRT Misidentification Probabilities
CASE 2: Spectrally Filtered DN Signals



(Normalization to adjust for differences in calibration factor or viewing geometry for redundant sensors does not affect the operability of the SPRT). The third subplot in each figure shows pointwise differences of signals DND-A and DND-B. It is this difference function that is input to the SPRT algorithm. Output from the SPRT is shown for a 250-second segment in the bottom subplot in each figure. Interpretation of the SPRT output is as follows: When the SPRT index reaches a lower threshold, A, one can conclude with a 99% confidence factor that there is no degradation in the sensors. For this demonstration A is equal to -4.60, which corresponds to false-alarm and missed-alarm probabilities of 0.01. As the figures illustrate, each time the SPRT reaches A it is reset to zero and the surveillance continues.

If the SPRT index drifts in the positive direction and exceeds a positive threshold, B, of +4.60, then it can be concluded with a 99% confidence factor that there is degradation in at least one of the sensors. Any triggers of the positive threshold are signified with diamond symbols in Figs. 4 and 5. In this case, since we can certify that the detectors were functioning properly during the time period our signals were being archived, any triggers of the positive threshold are false alarms.

If we extend sufficiently the surveillance experiment illustrated in Fig. 4 we can get an asymptotic estimate of the false alarm probability α. We have performed this exercise using 1000-observation windows, tracking the frequency of false alarm trips in each window, then repeating the procedure for a total of 16 independent windows to get an estimate of the variance on this procedure for evaluating α. The resulting false-alarm frequency for the raw, unfiltered, signals is $\alpha = 0.07330$ with a variance of 0.000075. (The very small variance shows that there would be only a negligible improvement in our estimate by extending the experiment to longer data streams). This value of α is significantly higher than the design value of $\alpha = 0.01$, and illustrates the danger of blindly applying a SPRT test to signals that may be contaminated by excessive serial correlation.

The computations shown in Fig. 5 employ the complete ST2 algorithm. When we repeat the foregoing exercise using 16 independent 1000-observation windows we obtain an asymptotic cumulative false-alarm frequency of 0.009142 with a variance of 0.000036. This is less than (i.e. more conservative than) the design value of $\alpha = .01$, as desired.

It will be recalled from the Introduction that we have used the eight most prominent harmonics in the spectral filtration stage of the ST2 surveillance algorithm. By repeating the foregoing empirical procedure for evaluating the asymptotic values of α, we have found that eight modes are sufficient for all of the expert system input variables shown in Table I. Furthermore, by simulating subtle degradation in individual signals, we have found that the presence of serial correlation in raw signals gives rise to excessive missed-alarm probabilities as well. In this case spectral whitening is equally effective in ensuring that pre-specified missed-alarm probabilities are not exceeded using the ST2 surveillance software.

SUMMARY

In summary, an ST2 technique has been devised which integrates frequency-domain filtering with sequential testing methodology to produce a compact algorithmic structure that provides a computationally tractable solution to a problem that is endemic to nuclear-plant signal surveillance. We have found the ST2 module to provide a valuable tool in ANL's ongoing development of innovative expert system tools for sensor-operability surveillance applications in nuclear plants, as well as in non-nuclear industrial applications that require high-reliability, high-sensitivity parameter surveillance.

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