CONF-800607--46

DETECTION OF SENSOR FAILURES IN NUCLEAR PLANTS USING ANALYTIC REDUNDANCY*

M. Kitamura**

Oak Ridge National Laboratory
Oak Ridge, Tennessee 37830

---

*Research performed under Subcontract No. 2476 with the University of Tennessee under Union Carbide Corporation contract W-7405-eng-26 with the U. S. Department of Energy.

**Visiting research associate from Tohoku University, Sendai, Japan, to the Department of Nuclear Engineering, The University of Tennessee, Knoxville, Tennessee 37916.

A method for on-line, nonperturbative detection and identification of sensor failures in nuclear power plants was studied to determine its feasibility. This method is called analytic redundancy, or functional redundancy.[1,2] Sensor failure has traditionally been detected by comparing multiple signals from redundant sensors, such as in two-out-of-three logic. In analytic redundancy, with the help of an assumed model of the physical system, the signals from a set of sensors are processed to reproduce the signals from all system sensors.

The concept of analytic redundancy can be realized in a variety of forms depending on one's purpose and his knowledge of the system under study. One realization is shown in Fig. 1; its key element, the estimator, was designed using the theory of Kalman filtering because of its simplicity of implementation. Each estimator is designed to work on a single-variable observation so that the comparison logic can take the form of simple, majority-vote logic.

We assume that the physical system can be represented by a linear, time-invariant mathematical system:

$$X(k + 1) = AX(k) + BU(k) \tag{1}$$

and

$$y_i(k) = C_iX(k) + v_i(k), \; i = 1,2,\ldots, m , \tag{2}$$

where X is an n-dimensional vector of state variables, and y_i is the ith of m observation variables. System noise vector U and measurement noise v_i satisfy the following conditions: $E[U(k)] = 0$, $E[v_i(k)] = 0$, $E[U(k)U^T(j)] = Q\delta_{kj}$, and $E[v_i(k)v_i(j)] = \sigma_i^2\delta_{kj}$, where C_i is a (1,n) observation matrix. For each y_i, the estimator is given by the following recursive algorithm:

$$\hat{X}(k+1|k) = A\hat{X}(k|k-1) + K(k)\left[C_i P(k|k-1)C_i^T + \sigma_i^2\right]^{-1}\left[y_i(k) - C_i\hat{X}(k|k-1)\right] , \quad (3)$$

$$K(k) = AP(k|k-1)C_i^T , \quad (4)$$

and

$$P(k+1|k) = AP(k|k-1)A^T + BQB^T - K(k)\left[C_i P(k|k-1)C_i^T + \sigma_i^2\right]^{-1} K^T(k) , \quad (5)$$

where $\hat{X}(k+1|k)$ represents the estimated value of X at time (k+1) based on past observations up to time (k), K(k) is the filter gain for the estimator, and P(k+1|k) is the estimated variance of $\hat{X}(k+1|k)$. With empirically determined initial estimates for $\hat{X}$, P, Q, and σ_i^2, the algorithm provides a successive estimation of X(k).

The feasibility of the method was studied with a simulation model for a commercial pressurized water reactor (PWR). A 10th-order simulation model[3] was shown to adequately represent the PWR dynamics by comparison to results obtained from a 50th-order model.[3] The model was then decoupled to two subsystems (core dynamics and steam generator dynamics) to simplify computational complexity and to increase the detectability of sensor failures; however, the performance of the sensor failure detection algorithm was examined both for the overall and decoupled systems. An example of the results for the decoupled steam generator subsystem dynamics (having variables of hot-leg temperature, cold-leg temperature, primary water temperature within the steam generator, steam generator tube temperature, and pressure in the steam generator secondary loop) is shown in Fig. 2 for a simulated pressure sensor failure (in this case, an abrupt 20% decrease in sensor sensitivity).

Figure 2 plots the algebraic difference between cold-leg temperature, T_{cl}, as estimated both from hot-leg temperature and from secondary loop pressure. A significant increase in the magnitude of this difference following the occurrence of the simulated failure (time ∿50 s) indicates the feasibility of detecting such a change in sensor characteristics.

Additional studies, involving other simulated sensor failure modes (alteration of signal rise time, signal clipping, various degrees of sensitivity change) as well as other sensors, led to the following conclusions:

1. Detection and identification of the failed sensor by analytic redundancy is feasible. In most simulated sensor failure cases, the $\hat{X}$ estimated from the failed sensor reading showed significantly different behavior from the other $\hat{X}$'s.
2. Because the difference between $\hat{X}$'s from failed and normal sensors changes in character depending on the type of failure, the detection logic design will require special care to provide adequate detection sensitivity for all likely failure modes.
3. Order reduction and/or decoupling of the system of equations is a key to successful application of the analytic redundancy method.
4. On-line, real-time implementation of the analytic redundancy method appears to be feasible for a five-variable system and a sampling interval of 0.5 s.

It should be stressed that the scheme of Fig. 1 is only one trial realization of various possible schemes. Other versions, providing greater sensitivity and decreased calculational complexity, are under study.

REFERENCES

1. R. N. Clark, "Instrument Fault Detection," *IEEE Trans. Aero. Elect. Sys.* AES-14, 456-465 (1978).

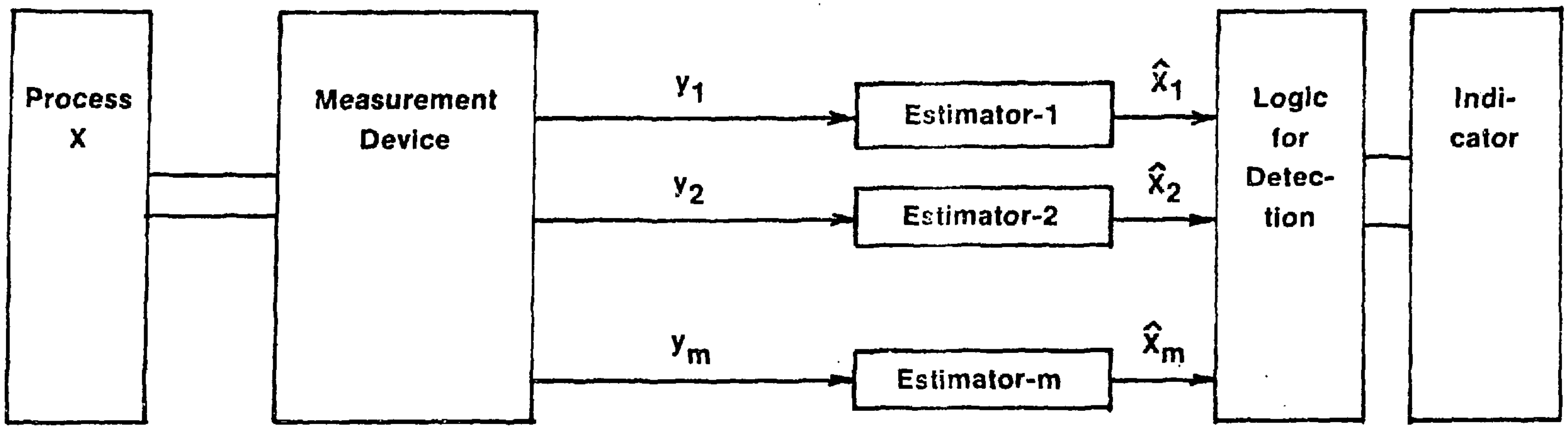
2. T. B. Cunningham and R. D. Poyneer, "Sensor Failure Detection Using Analytic Redundancy," *Proc. 1977 Joint Auto. Conf.* 1, 278-287 (1977).

3. J. D. Freels, "An Investigation of High Order and Low Order Dynamic Modeling of a Complete Pressurized Water Reactor Nuclear Power Plant," MS Thesis, The University of Tennessee, June 1979.

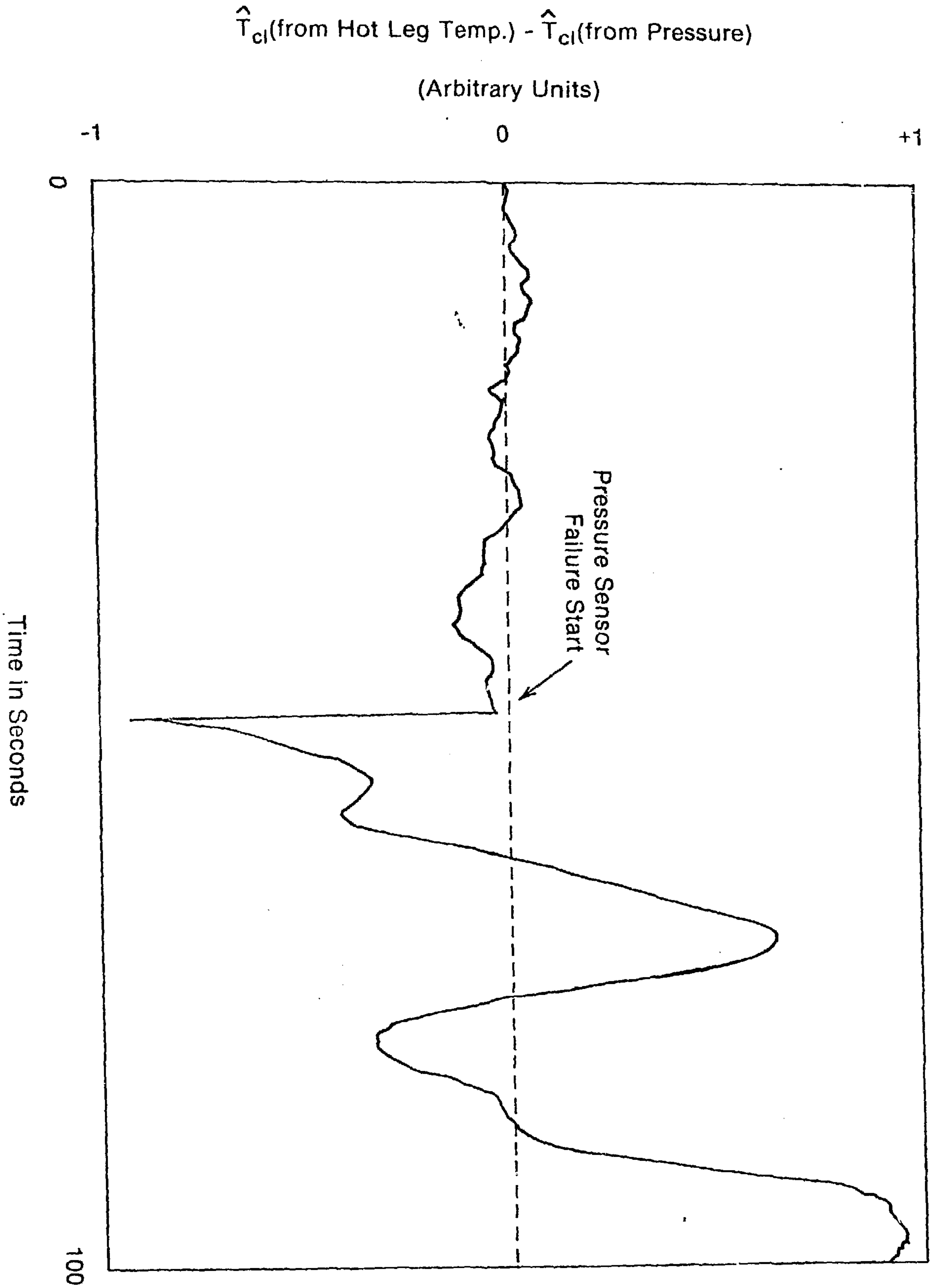
FIGURE CAPTIONS

Fig. 1. Diagram of scheme for sensor failure detection.

Fig. 2. Time trace of difference in estimated cold-leg temperature before and after a postulated pressure sensor sensitivity decrease of 20%.



Process
X
Measurement
Device
y_1
y_2
y_m
Estimator-1
Estimator-2
Estimator-m
$\hat{x}_1$
$\hat{x}_2$
$\hat{x}_m$
Logic
for
Detec-
tion
Indi-
cator



$\hat{T}_{cl}$(from Hot Leg Temp.) - $\hat{T}_{cl}$(from Pressure)
(Arbitrary Units)
-1
0
+1
0
100
Time in Seconds
Pressure Sensor Failure Start