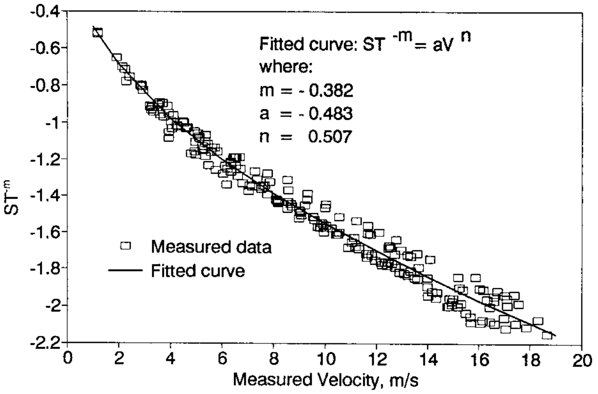

Fig. 1. TTA data correlation for a range of temperatures.

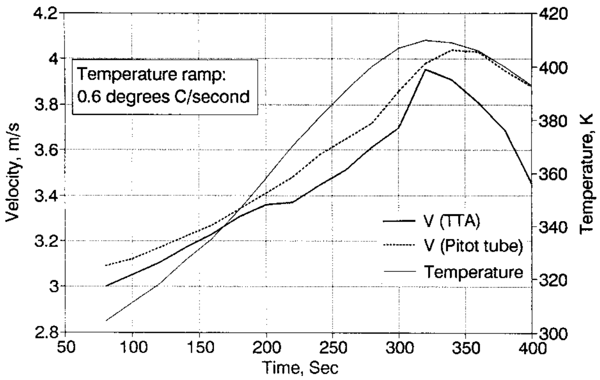

Fig. 2. TTA velocity measurement compared with a Pitot tube reference standard during a temperature ramp.

initially ~3 m/s and was increased to ~4 m/s by the end of the temperature transient. In general, the difference between the velocity deduced from the TTA and by the Pitot tube was of the order of ±10%.

It is concluded that the TTA can be used as a flow measuring device and that it may be used to measure flow velocity in a medium with a steadily varying temperature, using correlations obtained from data taken at constant temperature.

---

1. J. L. BAILEY et al., "Evaluation of the Performance of a Thermal Transient Anemometer," accepted for publication, *J. Experiments Fluids.*

5. Extended Kalman Filter Sensor Failure Detection Method for Pressurizer Monitoring, *Eduardo O. Assumpção Filho, Horácio Nakata (IPEN-CNEN/SP-Brazil)*

This work presents the development of the sensor failure detection and isolation system (FDIS) methodology, which is suitable for implementation in nuclear plant control systems. The methodology is based on the extended Kalman filter applied to a pressurized water reactor pressurizer. The utilization of the Kalman filter follows the standard procedure: First, an estimate of the state variables and the corresponding covariances are obtained; then, based on the state equations, the estimated state variables are propagated until the next measurement for the new estimate.

The state variables are estimated with the following equations:

$$x^+_{t_{i-1}} = x^-_{t_{i-1}} + K(z - Hx^-_{t_{i-1}})$$

and

$$P^+_{t_{i-1}} = P^-_{t_{i-1}} + KHP^-_{t_{i-1}} ,$$

where

$$K = P^-_{t_{i-1}} H^T (HP^-_{t_{i-1}} H^T + R)^{-1} .$$

The propagation is performed with the following equations:

$$x_{t_i} = \boldsymbol{\phi}(t_i, t_{i-1}) x_{t_{i-1}} + \boldsymbol{\theta}(t_i) u(t_i)$$

and

$$P_{t_i} = \boldsymbol{\phi}(t_i, t_{i-1}) P_{t_i} \boldsymbol{\phi}^T(t_i, t_{i-1}) + Q ,$$

where

$$P_{t_i} = (I - KH) P_{t_{i-1}} .$$

Thus, one can define a residue r_{ti} as

$$r_{t_i} = z_i - Hx_{t_i} .$$

All preceding terms follow the conventional definitions given in Ref. 1.

The filter described previously is in the extended mode[2] because the matrices $\boldsymbol{\phi}$ and $\boldsymbol{\theta}$ are related to the state variables through the system state equations, which represent the modeling approximations to the pressurizer behavior. The equations are based on conservation laws, with the assumption of equilibrium for the liquid and vapor in the homogeneous mixture at the saturation temperature in the pressurizer.

The current FDIS is based on residual sequence monitoring during the pressurizer operation. The residual sequence is a white gaussian sequence of mean zero and covariance given by $(HP_{t_{i-1}}H^T + R)$. During the filter operation, the residual sequence is monitored, and the degree of its deviation from the expected distribution is used to trigger the failure signal. The residue distribution during normal operation, operation transitions included, is previously monitored, and a background level below which no failure triggering is allowed is determined for each sensor measurement. When a residue deviates consistently from the expected gaussian distribution during the mon-

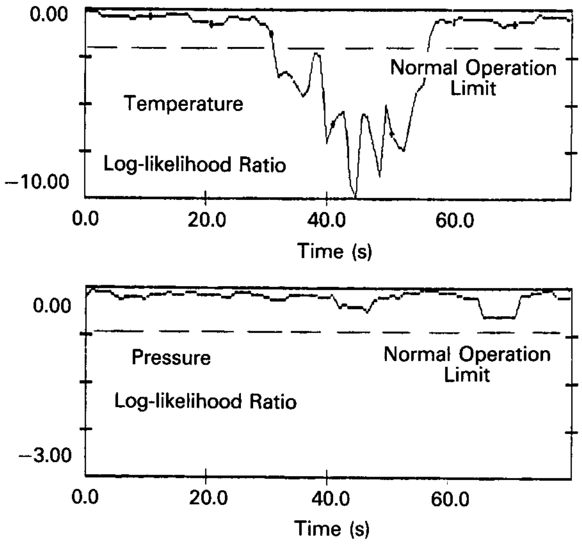

Fig. 1. Random noise perturbation in the temperature signal between 30 and 50 s.

itoring period, the sensor failure is signaled. If the violation only occurs in one component of the residue vector, a failure in the corresponding sensor can be declared. If consistent deviations in two or more components are detected, the probability of a system malfunction is high.

The current FDIS has been tested against LOFT transient data.[3] The results obtained were consistent with the experimental data for temperature, pressure, and water-level sensors. Key modeling parameters were adjusted to construct the extended Kalman filter.

The FDIS developed here showed high reliability during the simulation of most representative failure types, e.g., the failure simulation by superposing a ramp, a step, or a random noise perturbation on the normal operation signals. Figure 1 illustrates the log-likelihood ratio[4] during the addition of a gaussian random noise perturbation in the temperature sensor between 30 and 50 s, with the standard deviation of $4\sigma_t$ in magnitude, where σ_t is the thermocouple signal standard deviation during normal operation. The temperature log-likelihood ratio curve peaks sharply during the transient, between 30 and 50 s, while the pressure log-likelihood ratio behaves smoothly, not trespassing the normal operation level. Similarly, in numerical tests for the pressure and water-level sensor failure simulations, the detection and isolation of the failed sensor has been found to be highly effective, signaling a failure in a very short time period. In general, a relatively small sensor perturbation can be detected and isolated with the FDIS developed here, discriminating from high background noise or from spurious malfunctions.

---

1. R. N. CLARK, B. CAMPBELL, "Instrument Fault Detection in a Pressurized Water Reactor Pressurizer," *Nucl. Technol.*, **56**, 23 (1982).
2. A. H. JAZWINSKI, *Stochastic Processes and Filtering Theory*, Academic Press, New York (1970).
3. J. L. TYLEE, "Real-Time Instrument Failure Detection in the LOFT Pressurized Water Reactor Pressurizer," EGG-EE-5518, EG&G Idaho Inc. (1982).
4. P. S. MAYBECK, *Stochastic Models Estimation and Control*, Vol. 1, Academic Press, New York (1979).