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CONF-811206--5

DE82 005486

Conf-811206--5

ON-LINE VALIDATION OF LINEAR-PROCESS MODELS USING GENERALIZED LIKELIHOOD RATIOS

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Abstract

A real-time method for testing the validity of linear models of nonlinear processes is described and evaluated. Using generalized likelihood ratios, the model dynamics are continually monitored to see if the process has moved far enough away from the nominal linear model operating point to justify generation of a new linear model. The method is demonstrated using a seventh-order model of a natural circulation steam generator.

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Prepared for presentation at the 20th IEEE Conference on Decision and Control, San Diego, California, December 16-18, 1981.

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Introduction

In recent years, the application of linear optimal estimation and control theory to large dynamic processes has been an active area of research. At the Idaho National Engineering Laboratory, several projects [1,2,3,4] have indicated that using these advanced theories can result in improved safety and availability at nuclear power plants. In current work developing an instrument failure detection system for a natural circulation steam generator, difficulties have arisen in that a fixed linear model cannot adequately describe the complex dynamics of the steam generator during transient excursions. To overcome this inadequacy, it is necessary to provide the on-line capability of generating a new linear model when it has been determined that the process dynamics have moved sufficiently away from the nominal point upon which the linear model is based. How to determine when such a relinearization is required is the subject of this paper.

The generalized likelihood ratio (GLR) technique [5] is a powerful method for detecting and identifying sudden changes (failures) in process dynamics. By applying statistical tests to the innovations sequence of a Kalman filter designed for the nominal system, the GLR method can detect and identify failure type, failure time, and failure magnitude. In this paper, using a linear steam generator model as an example, the GLR approach is specifically used to detect large changes in the state and input vectors of the model. The detection of such changes is used as a criterion for developing a new linear model based on current state and input estimates.

Generalized Likelihood Ratio Technique

We assume a linear, shift-invariant discrete system described by:

$$x(k+1) = \Phi x(k) + \Theta u(k) + v(k) \tag{1}$$

$$y(k) = Cx(k) + Du(k) + w(k) \tag{2}$$

where $x(k)$ is the state vector, $u(k)$ a deterministic input vector, $y(k)$ the output vector, and $v(k)$ and $w(k)$ are zero-mean white processes. The innovations sequence of a Kalman filter designed for this system is itself a white process with variance $V(k)$:

$$V(k) = CP(k|k-1)C^T + R \tag{3}$$

where $P(k|k-1)$ is the state estimate error covariance matrix at time k prior to updating the estimate with a measurement and R is the covariance of $w(k)$.

The details of the GLR technique are outlined in [5]; what is presented here is a simple description of the method. Briefly, the GLR approach tests the innovations sequence to see if its statistical characteristics match those of $V(k)$ in (3). The measure used to perform this test is the log-likelihood ratio:

$$l(k) = \ln\left[\frac{p(\gamma|H_i)}{p(\gamma|H_0)}\right] \tag{4}$$

where $p(\gamma|H_0)$ is the probability density function of the innovations γ for the no failure hypothesis H_0, while $p(\gamma|H_i)$ is the probability density function of γ for failure hypothesis i. So in the GLR, at each time step several failure types are hypothesized, e.g. in this study, jumps and steps in x(k) and u(k), and for each failure type, a value of l is computed. The largest value of l then indicates which failure type is most likely to have occurred. Comparing l_{max} to some predetermined threshold then yields the failure decision:

$$l_{max}(k) \underset{H_0}{\overset{H_i}{\gtrless}} \varepsilon \tag{5}$$

In applying this method to determine the validity of the steam generator model, we first note that the linear steam generator model matrices Φ, Θ, C and D (see equations (1) and (2)) are determined by linearizing the nonlinear process dynamics about some nominal operating point $(\overline{x},\overline{u})$. If at time k by using the failure decision described by (5), a change (failure) in the plant state or input vector is detected, a new operating point defined by the current state estimate $\hat{x}(k)$ and the input u(k) is established and new system matrices are computed. By continually updating, or relinearizing the model in this manner, the model validity is no longer suspect if the plant state moves far from nominal.

Steam Generator Model Simulation Results

In most nuclear power plants, heated water (primary coolant) from the reactor flows through a steam generator to create the steam required by the plant turbines. Water depleted by the steam generation process is replaced by an automatically controlled feedwater system. Figures 1 through 4 show the simulated response of the Loss-of-Fluid Test (LOFT) reactor plant, located at the Idaho National Engineering Laboratory, to a loss of the pumps supplying this feedwater. The simulated test data was obtained using a nonlinear model of the entire LOFT plant [6] and the state estimates obtained using a Kalman filter incorporating a seventh-order linear model of the steam generator.

The loss of feedwater results in less heat being extracted from the primary coolant resulting in the pressure increase seen in Figure 1. The change in slope in the pressure curve at about 24 seconds is due to a manual shutdown of the reactor at that time. Following shutdown (scram) of the reactor, the valve controlling the steam flow from the steam generator closes until the pressure reaches a shutdown operating band of 920 to 1120 psia--this throttling action is noted in Figure 1. Also seen in Figure 1 are the Kalman filter estimates of the pressure response provided by a fixed linear model and by using linear models generated using the GLR approach. For the pressure curve, the fixed linear model is seen to be totally inadequate. The relinearized model estimate (two new models were generated during the transient at 18 and 39 seconds) is a vast improvement, especially in predicting the new steady state pressure.

The corresponding changes in steam generator water level and steam flow due to the feedwater loss is seen in Figures 2 and 3. Note the effect of the plant scram at 24 seconds, i.e. the change in the slope of the water level decrease and the shutoff of steam flow due to the previously mentioned steam valve throttling. In these two figures, the superiority of using relinearized models in the Kalman filter is again demonstrated.

Figure 4, which shows the feedwater flow and the two estimates during the transient, dramatically illustrates the inadequacy of a fixed linear model. Following the loss of the feedwater pumps, the feedwater control system senses a need for more feed flow and completely opens the feedwater valve in an attempt to meet this need. Obviously, without the pumps, no matter how far the valve is opened, no feed flow will be forthcoming, yet we see the fixed linear model interprets the valve opening as an increase in flow. Using the GLR relinearization technique, it is seen that with the first model change at 18 seconds, the relinearized model estimate matches the test data exactly.

Finally, Figure 5 shows the maximum log-likelihood ratio computed by the GLR method during the feed flow loss transient. We see that the ratio quickly grows upon transient initiation and for the fixed model remains high due to the large biases in the estimates seen in Figures 1 through 4. For the relinearized model, the same initial growth in the ratio is noted but following the generation of a new model at 18 seconds (a threshold value of ε=30 was employed) quickly drops back to near zero. The plant scram at 24 seconds causes another transient in the steam generator, hence the ratio begins to increase but drops once a new model is generated at 39 seconds. In this scheme, a 10 second "detection window" as described by Willsky [5] was used to insure accurate failure identification. Hence, once a failure was detected using equation (5), a delay of 10 seconds was implemented to insure the failure was indeed due to a change in the state or input vector and not a measurement (or plant) failure. Similarly, following generation of a new model, 10 seconds elapse before testing for further failures to allow time for the identified failure to exit the detection window. Adjusting the size of this window will affect the performance of the GLR technique.

Conclusions

In this paper, we have seen that the inaccuracies associated with being restricted to linear models in applying optimal estimation and control theories can be eliminated by using a generalized likelihood ratio to test the model validity. If the computed ratio exceeds a threshold value, a new linear model based on the current plant state estimate and input vector can be generated on-line, improving the model performance substantially.

In the specific application described here, a natural circulation steam generator, implementing this model validation technique was a simple task. A Kalman filter estimator and GLR computation had previously been developed for the steam generator in designing a scheme for detecting and identifying instrument failures, i.e. sudden changes in the output vector $y(k)$. It was easy to modify the GLR routines to include the capability of also detecting changes in $x(k)$ and $u(k)$ as required by the method outlined here. This modification has the added benefit that if a plant operator using this system noted a sudden change in some reading being monitored, the GLR scheme could distinguish between a hardware failure and an inherent change in the plant dynamics, and immediately display this decision. If the failure were due to an instrument malfunction, information as to which instrument failed, how it failed, when it failed, and the failure magnitude could be provided. Such information could prove invaluable to a plant operator.

Acknowledgement

This work supported by the U. S. Nuclear Regulatory Commission, Office of Reactor Safety Research under DOE Contract No. DE-AC07-76ID01570.

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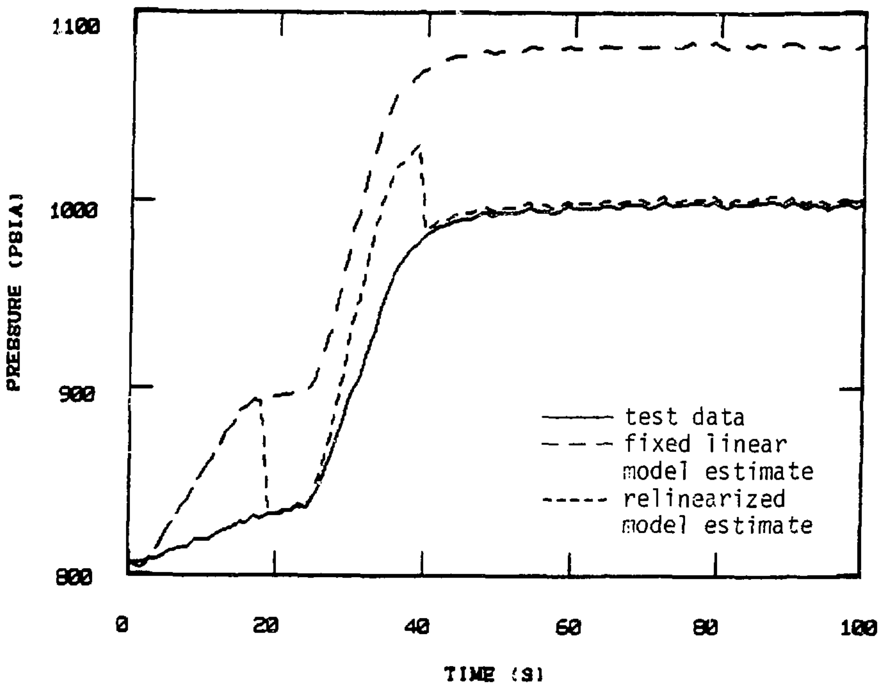

Figure 1. Feed flow loss transient, pressure response

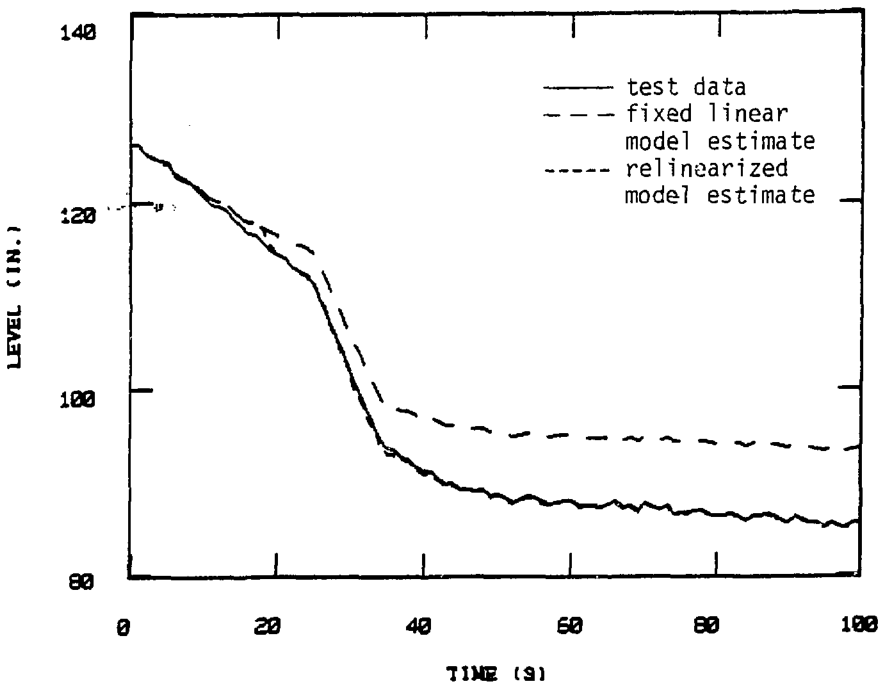

Figure 2. Feed flow loss transient, water level response

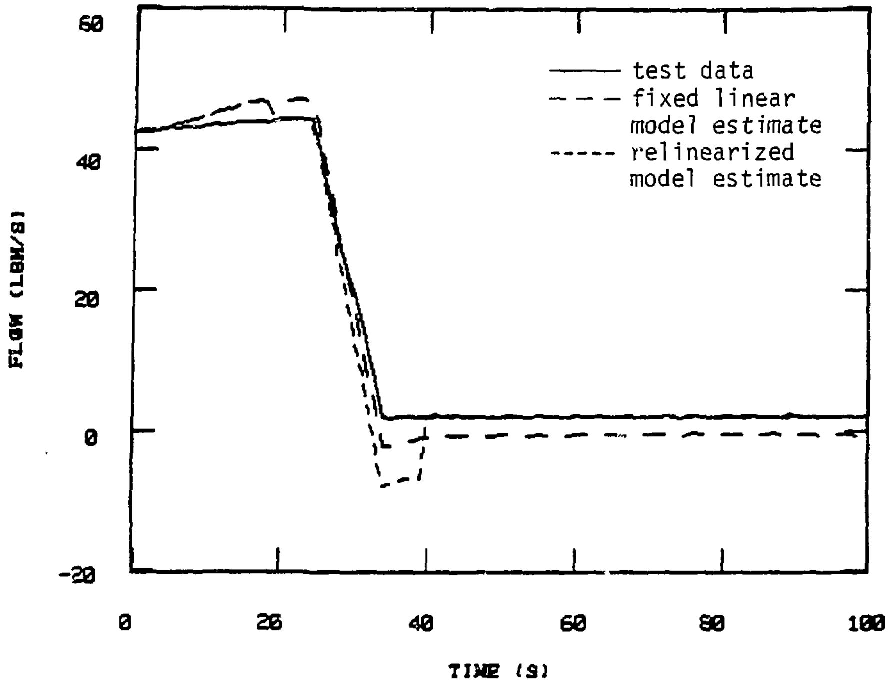

Figure 3. Feed flow loss transient, steam flow response

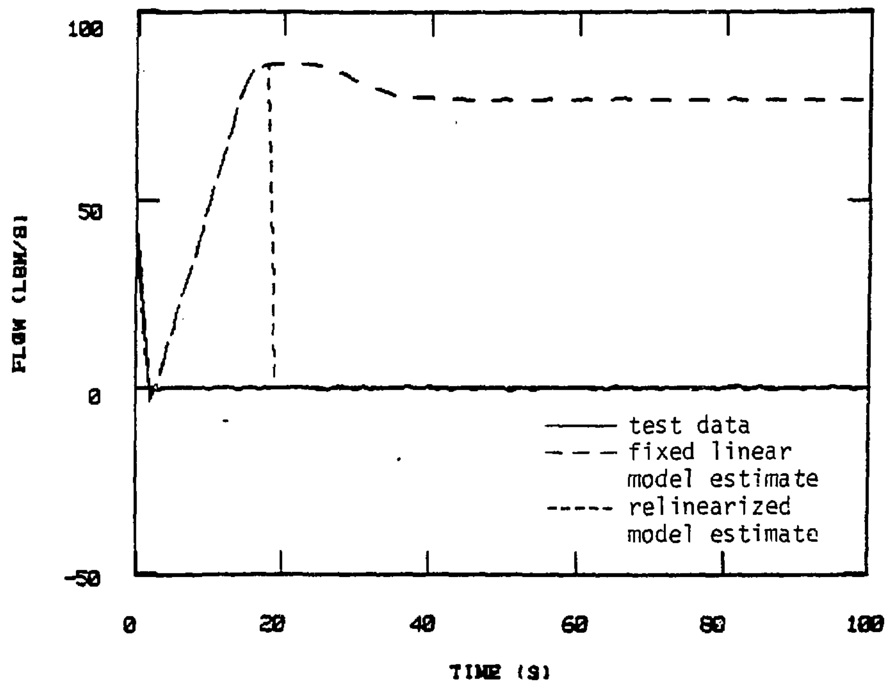

Figure 4. Feed flow loss transient, feed flow response

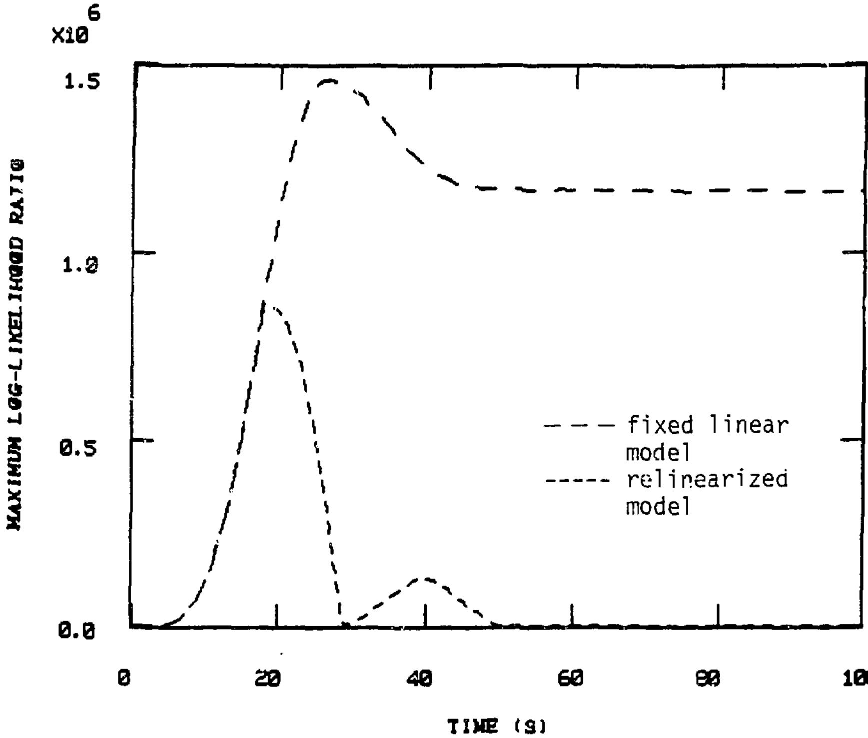

Figure 5. Feed flow loss transient, maximum log-likelihood ratio