CONF-970765

ANL/RA/CP -- 92110

CONF-970765--2

Paper to be presented at the 9th International Conference on Intelligent Systems Applications to Power Systems (ISAP'97) Seoul, Korea, July 6-10, 1997

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* Work supported by the U.S. Department of Energy, Energy Research Programs under Contract W-31-09-ENG-38.
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Application of a Model-based Fault Detection System to Nuclear Plant Signals

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ABSTRACT - To assure the continued safe and reliable operation of a nuclear power station, it is essential that accurate online information on the current state of the entire system be available to the operators. Such information is needed to determine the operability of safety and control systems, the condition of active components, the necessity of preventative maintenance, and the status of sensory systems. To this end, ANL has developed a new Multivariate State Estimation Technique (MSET) which utilizes advanced pattern recognition methods to enhance sensor and component operational validation for commercial nuclear reactors. Operational data from the Crystal River-3 (CR-3) nuclear power plant are used to illustrate the high sensitivity, accuracy, and the rapid response time of MSET for annunciation of a variety signal disturbances.

Key Words:
Fault detection, signal validation, plant monitoring, surveillance

Introduction and Background

The essence of the MSET method relies upon an examination of the totality of information available from the array of sensors used to monitor the system and a comparison of these data as a whole to similar sets of data collected from the same system operated at various conditions in the past. Based upon this comparison of the current condition of the system with it's past history, an optimal estimate of the current state of the system is obtained even if there are errors in the data currently collected, i.e. some of the sensors have malfunctioned.

Having an estimate of the true current state of the system, the differences between this estimate and the current measurements are analyzed using an extremely sensitive pattern recognition technique, the sequential probability ratio test (SPRT), for automatic annunciation of discrepant signals or the onset of degradation in sensors or reactor components. Conventional parameter-surveillance schemes are sensitive only to gross changes in the process mean, or to large steps or spikes that exceed some threshold limit check. The SPRT provides a superior surveillance tool because it is sensitive not only to disturbances in signal mean, but also to very subtle changes in the statistical quality (variance, skewness, bias) of the monitored signals.

For slowly evolving degradation modes (gradual decalibration bias in a sensor, wearout or buildup of a radial rub in rotating machinery, build-in of a radiation source in the presence of a noisy background signal, loss of time response in a pressure transmitter, etc), the SPRT can provide annunciation of the incipience or onset of the disturbance long before it would be apparent to visual inspection of CRT signal traces, and well before conventional threshold limit checks would be tripped. This permits the operator to terminate or avoid events that could otherwise result in challenges to plant safety margins or system availability goals, and, in many cases, to schedule corrective actions (sensor replacement or recalibration; component adjustment, alignment, or rebalancing; etc.) to be performed during a scheduled plant outage.

A companion paper in this Conference [1] reports the theoretical foundations and algorithmic design of the MSET method. The purpose of this paper is to report the results of a collaborative effort between ANL and the Florida Power Corp. to configure and test ANL's new MSET system using signals from Florida Power's Crystal River-3 (CR-3) PWR.

Application to PWR Plant Signals

ANL and FPC have been engaged in a collaborative study since 1992 to investigate the use of MSET for a variety of surveillance applications that include signal validation, instrument calibration monitoring, and early detection of component operability degradation. For the examples reported here, actual plant signals were taken from archive optical disks from the 18 month operating cycle spanning from June of 1992 through Dec. of 1993.

Venturi Flowmeter Surveillance with MSET

One of the primary objectives of nuclear power plants is the efficient operation of plant systems, thereby reducing the cost of electricity. Accurate determination of the thermal power of the plant is required to minimize the cost per unit of energy produced. The feedwater flow rate to the steam generators is one of the primary quantities used for the thermal power calculation [Ref. 2]. However, the accuracy of the flow meters that measure the feedwater flow rate deteriorates over time resulting in flow rate measurements that are higher than their actual values, thus yielding artificially high thermal powers [ref. 3]. U. S. NRC licensing rules require that a reactor be operated at or below the rated power for the reactor. Since these rules also require that the calculated thermal power be used when setting the operating conditions of the plant, the real power produced by a reactor hampered by inaccurate feedwater flow measurements will be less than the power rating for the reactor. A 2% power derating costs a utility about $20,000 per day, or 7.3 $M per yr, in lost revenue for an 800 MWe unit at an energy cost of $0.05 per kW-hr [ref. 3].

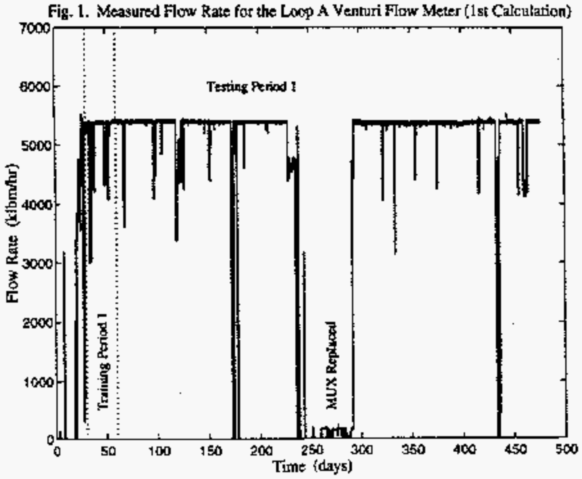
Venturi flow meters are commonly used to measure the feedwater flow rate in nuclear power plants. The flow meters consist of a short section of constricted flow area piping (the venturi surface) that is inserted between two flanges in the feedwater pipe. The constriction accelerates the fluid and temporarily lowers its static pressure. Pressure gauges are used for measuring the pressure drop between the inlet and constricted regions of the flow meter. Fluid flow rate is directly related to the pressure drop. The accuracy of venturi flow meter measurements decreases with time though, due to a chemical reaction between the surface coating of the flow meter and the feedwater. The fouling of the venturi surface with reaction products results in flow measurements becoming 1% - 2% higher than the actual flow [ref. 4]. The fouling problem has been observed to develop rapidly, after as little as 2 months of operation with a clean venturi flow meter. During long shutdown periods of the reactor, the feedwater flow meters are cleaned and recalibrated. But since the long shutdown periods occur at the end of a reactor operating cycle, which typically lasts for 18-24 months, reactors can spend most of their normal operating time with fouled feedwater flow meters.

We have used the MSET system to model the feedwater flow meter as a function of dissimilar process variables dynamically related to the feedwater flowrate. When trained with reliable data, the MSET model can estimate the correct flowrate regardless of the changes in the physical state of the flow meter, since the model's estimates are based on the behavior of the system as a whole.

The MSET system is used to model one of the two feedwater flow meters in Florida Power's CR-3 power plant. The two feedwater flow meters are located in the piping that supplies condensate water to the loop A and B steam generators. Because the two loops contain identical components, only the feedwater flow meter in loop A has been modeled by MSET for the present investigation. The MSET model utilizes data from 15 diagnostic sensors in loop A. In addition to the flowrate data from feedwater flow meter A, the model utilizes signals from other loop A sensors including steam generator level indicators, steam line thermocouples, feedwater thermocouples, and the feedwater pump tachometer. The signals that are included in the model are those that are most highly correlated with the feedwater flow meter signal. For this analysis, only every 10th point recorded during the reactor cycle was used (i.e. one point every 10 minutes). But since the reactor run lasted 476 days, the total number of data points used in the analysis is over 68,000.

The MSET model was trained using data from the second month of the operating cycle (i.e., days 30 through 60). Fig. 1 shows the signal from the loop A feedwater flow meter for the whole of the operating cycle. The figure indicates which period of the reactor cycle was used to train the model and which period was used to test the model. Also indicated in Fig. 1 is a roughly 2 month period at the middle of the reactor run during which the feedwater signal was not archived. During this period, the reactor's data acquisition system was off-line due to the replacement of a multiplexor (MUX).

Fig. 1. Measured Flow Rate for the Loop A Venturi Flow Meter (1st Calculation)



In Fig. 2, the MSET calculation for the feedwater flow is shown. The calculated flowrate compares well with the flow meter measurements. In Fig. 3, the difference between the measured and calculated flowrates is shown. Note that the calculated and measured flowrates drift apart during the first 6 months of the testing period (days 60 to 220). This drift is due to the fouling of the flow meter, which causes it to report flowrates that are higher than the calculated flowrates.

Fig. 2. Calculated Flow Rate for the Loop A Venturi Flow Meter (1st Calculation)

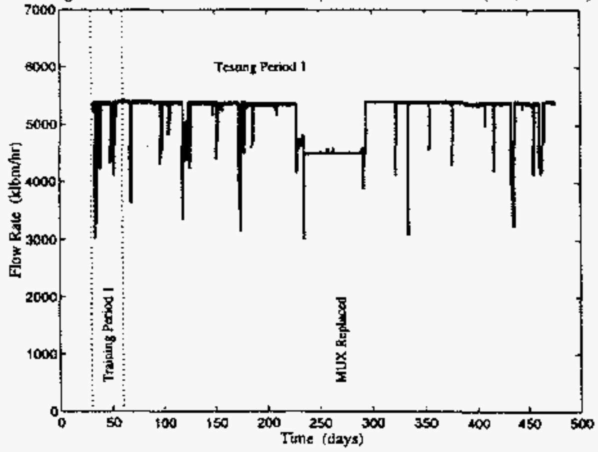
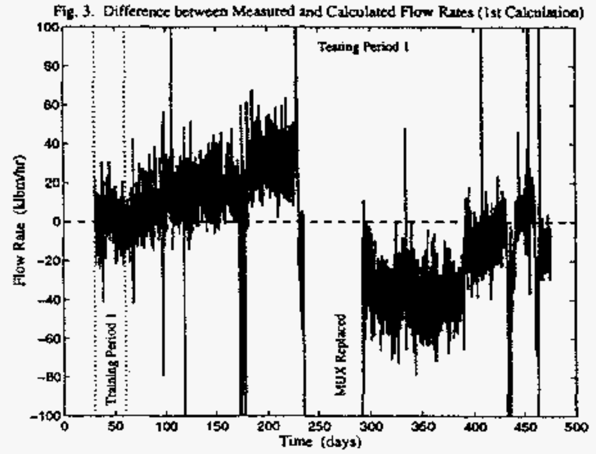
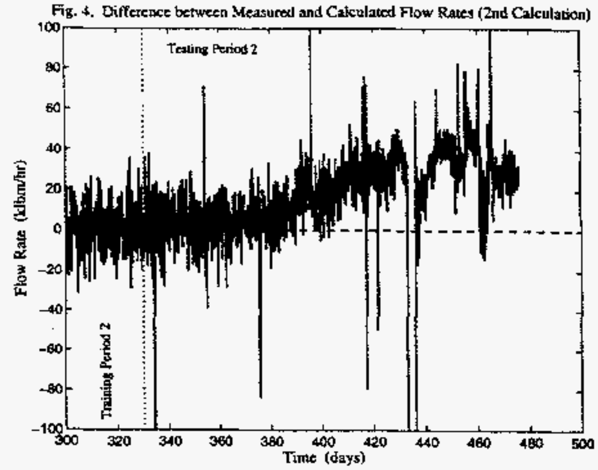


Fig. 3. Difference between Measured and Calculated Flow Rates (1st Calculation)



By the end of the first 6 months of the testing period, the measured flowrate is about 0.5% larger than the calculated flowrate. A discontinuity is evident between the response of the difference signal from before the period when the data archival system was taken off-line and the response from after the period. Immediately before the MUX was replaced, the measured flowrate is about 30 klbm/hr greater than the calculated flowrate, while immediately after the MUX was replaced, the measured flowrate is about 40 klbm/hr less than the calculated flowrate. The discontinuity is due to the recalibration of some of the sensors in the feedwater system. When the sensors used as inputs to the model are recalibrated, the model must be retrained since the earlier training patterns are no longer valid. To illustrate this point, a second calculation was performed in which only data recorded after the MUX replacement were used. Data from the eleventh month of operation (i.e., days 300 through 330) were used to train the model in the second calculation. In Fig. 4, the difference between the measured and calculated flowrates for the second calculation is shown. The second calculation reveals a drift of about 0.7% in the flow meter measurements during the later half of the operating cycle.

Fig. 4. Difference between Measured and Calculated Flow Rates (2nd Calculation)

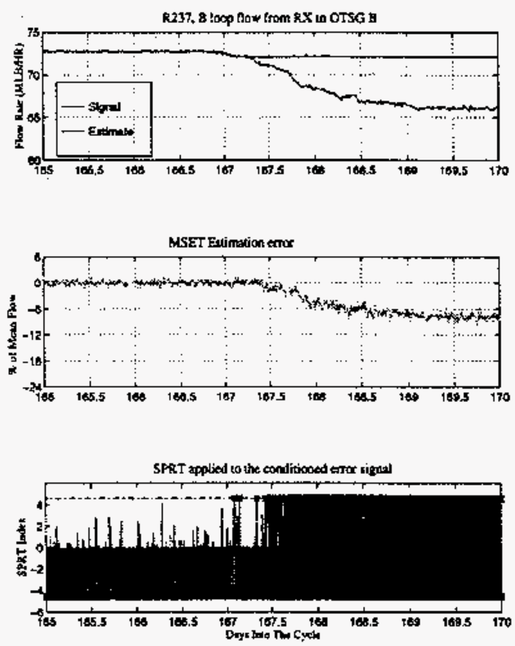


The MSET analysis has shown that the degradation of venturi flow meter measurements due to fouling of the venturi surface can be detected. The analysis of the Crystal River-3 data revealed a slow and steady degradation of the flow meter measurements during the 1992/1993 cycle.

Failure of a Flow Sensor

This second example is of a rapidly failing flow sensor in CR-3 that was taken from signal archives. The upper subplot in Fig. 5 shows data from sensor R237, the primary loop B flowrate, superimposed upon the MSET estimate for that signal. This flow sensor failed (i.e., its output dropped by about 5% in a several hour period) on day 167 in the reactor cycle. MSET was trained to recognize the normal behavior of the system in which this flow sensor was located and then used to monitor the system. It can be seen in Fig. 5 that the actual flow signal and the MSET estimate agreed quite well during the initial portion of the monitoring period. This is also indicated by the middle subplot, which shows the estimate error--or the difference between the measured and estimated flowrates. As observed in the upper subplot, the measured and estimated flow values clearly diverge after about T=167.5 d (a few percent difference). Indeed, if this signal was being closely watched, this failure would likely be detected by visual observation at this point. However, at T=167.1 d, a full 9 hours before the fault would become evident to visual observation, MSET starts to alarm (the lower subplot in Fig. 5), indicating that sufficient information has been obtained to confirm that a malfunction has occurred. A short time later, the fault is obvious where the measured signal decreases from its initial value of about 72 to about 70 while the estimated signal remains at it's initial value. The significance of the estimated value remaining where it does is quite important; this directly implies that despite the large change in the signal from the pressure sensor, the model has determined from the total collection of sensor data available that the system state has not changed and this sensor similarly should not change. Thus, it can be concluded that the fault is isolated to this particular sensor and that the process has not been affected. If this had been a safety critical sensor, the process could have been shut down prior to the loss of this sensor. However, it would also have been possible to utilize the estimated sensor reading from MSET to replace this faulted sensor and to continue operation of the process.

Fig. 5. Failure of R237, detected using MSET on day 167 of the cycle



Loss-of-Time-Response Failure

A loss-of-time-response failure in an instrument is one of the most difficult modes of failure to identify with conventional surveillance schemes during steady-state operation. In this mode of failure, which has been known to occur particularly with oil-filled pressure transmitters, the mean value of the signal may remain unchanged. The disturbance may show up only as a change in the dynamic response of the transmitter. Conventional trending programs that use simple threshold limits, and even parity-space methods that rely on the mean values of signals, may fail to identify this mode of failure.

One such failure was identified in CR-3 in January, 1993. The failed sensor was one of three redundant sensors. To illustrate the very high sensitivity of the SPRT method for identifying extremely subtle disturbances in sensors with incipient faults, Fig. 6 shows signal segments from two of the redundant sensors, R200 and R201. The data shown in were taken from mid-December of 1992, before the instrument degradation was observable to operations personnel. The middle subplot shows the residual function, which exhibits small fluctuations about a zero mean. The bottom subplot shows continuous SPRT alarms--even though no discrepancy is at all apparent to a visual inspection of the raw signals.

Fig. 6. (I) RPS-ES Rosemount Transmitter Time Constant Failure

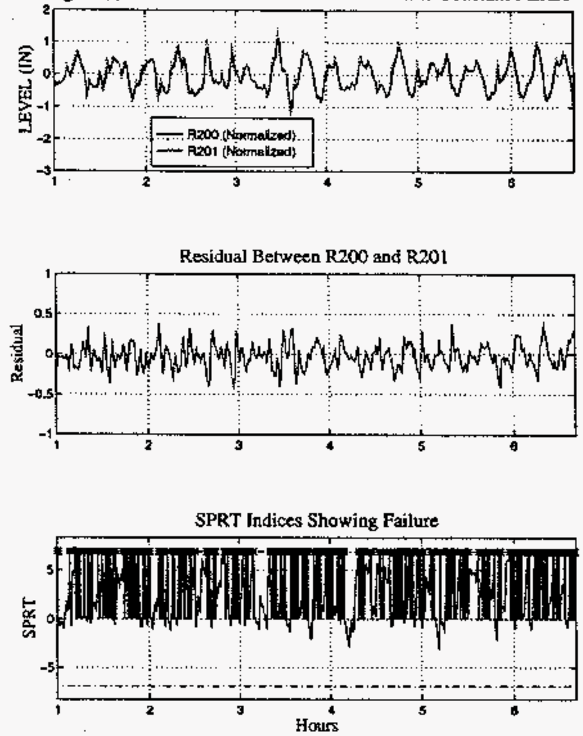


Fig. 7 shows the raw signals for redundant sensors R200 and R202 (upper subplot), the residual function (middle subplot), and the SPRT index (bottom subplot). Once again, SPRT alarms tripped continuously, indicating a sensor disturbance in R200 or in R202. Finally, Fig. 8 shows the same corresponding information for redundant sensors R201 and R202. Note that there are no SPRT alarms in the lower subplot of Fig. 8. The conclusion that can be drawn from the SPRT results in these three figures is that sensor R200 is failing.

To learn how much earlier degrading sensor R200 could have been identified by the SPRT method, archive signals were processed from several weeks before the sensor was confirmed to have failed. Fig. 9 summarizes the results from the SPRT calculations for the three redundant signal pairs. Note that for both signal pairs involving pressure transmitter R200, SPRT "signal degradation" alarms started tripping at a high frequency early in the figure. The SPRT for sensors R200 and R202 started to alarm on day 119 in the operating cycle, and for sensors R200 and R201 on day 120. These SPRT annunciation times corresponded to 10/19/92 and 10/20/92, respectively. This is a full three months before the degradation became observable to operations personnel.