Conf-911214--1

Paper to be presented at the International Conference on Plant Life Extension, Upgrading, Repair, Refurbishment, Uprating and Aging (PLEX 91), 2-4 December 1991, Berlin, Germany

ANL/CP--73414

DE92 004150

ADVANCED CONDITION MONITORING TECHNIQUES AND PLANT LIFE EXTENSION STUDIES AT EBR-II*

Ralph M. Singer
Kenny C. Gross

Argonne National Laboratory
9700 South Cass Ave.,
Argonne, Illinois 60439
USA

William H. Perry
Ronald W. King

Argonne National Laboratory
P. O. Box 2528
Idaho Falls, Idaho 83403-2528
USA

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

ADVANCED CONDITION MONITORING TECHNIQUES AND PLANT LIFE EXTENSION STUDIES AT EBR-II*

William H. Perry[1]
Ralph M. Singer[2]
Ronald W. King[1]
Kenny C. Gross[2]

ABSTRACT

Numerous advanced techniques have been evaluated and tested at EBR-II as part of a plant-life extension program for detection of degradation and other abnormalities in plant systems. Two techniques have been determined to be of considerable assistance in planning for the extended-life operation of EBR-II. The first, a computer-based pattern-recognition system (System State Analyzer or SSA) is used for surveillance of the primary system instrumentation, primary sodium pumps and plant heat balances. This surveillance has indicated that the SSA can detect instrumentation degradation and system performance degradation over varying time intervals and can be used to provide derived signal values to replace signals from failed sensors. The second technique, also a computer-based pattern-recognition system (Sequential Probability Ratio Test or SPRT) is used to validate signals and to detect incipient failures in sensors and components or systems. It is being used on the failed fuel detection system and is experimentally used on the primary coolant pumps. Both techniques are described and experience with their operation presented.

INTRODUCTION

A challenge that faces operators of mature nuclear power plants is the detection of incipient and long-term gradual degradation of sensors and components in order to avoid unplanned outages, to orderly plan for anticipated maintenance activities, to minimize challenges to the reactor protection system and to aid in the extended-life operation of a power plant. Ideally, the adopted solution should result in an increase in the availability of the plant, reduce unneeded maintenance activities and associated personnel exposures and provide long-term trending data for system performance characterization to identify potential ageing or other degradation phenomena. This paper will describe two advanced pattern-recognition-based techniques that have been applied to surveillance and monitoring activities at the Experimental Breeder Reactor No. II (EBR-II) power plant located at the Idaho National Engineering Laboratory.

---

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

[1]EBR-II Division, Argonne National Laboratory, Idaho Falls, ID, USA.

[2]Reactor Analysis Division, Argonne National Laboratory, Argonne, IL, USA.

Additional descriptive information can be found in the references listed at the end of this paper.

The first technique, named the System State Analyzer or SSA, is used to identify the current state of any system or sub-system of the plant based upon its previous operating history. The current state is determined by comparing a vector of sensor signals that are closely associated with the performance of the system under consideration with previously measured sets of the same signal vectors. This comparison by SSA is accomplished by software-based pattern-recognition algorithms that establish pertinent relationships between the signals within a defined operational domain. These learned patterns or relationships among the signals are then used to identify the learned state that most closely correspond with the current set of signals. This process of system state identification is used to detect and diagnose deviations in the operational characteristics of a plant system due to any cause. The SSA is presently being used to monitor the primary reactor coolant pumps and the core temperature rise in EBR-II.

The second technique, named the sequential probability ratio test or SPRT, is used to detect minute disturbances in the operation of an individual plant component or sensor through subtle changes in the statistical characteristics of the stochastic content of the signals. Although as presently formulated, this technique requires the presence of either redundant sensors on a single component or single sensors on duplicate components, it has been mathematically demonstrated that there can be no other procedure that has a lower error probability or shorter sampling time to detect a disturbance than SPRT. Experience gained with this system during the monitoring of the primary reactor coolant pumps at EBR-II prior to and during a impeller binding incident will be described.

DESCRIPTION OF THE EBR-II PLANT

The Experimental Breeder Reactor No. II (EBR-II) is a small electrical power producing, liquid-metal-cooled nuclear reactor located at the Idaho National Engineering Laboratory in Idaho and operated by Argonne National Laboratory for the US Department of Energy. Its nuclear steam supply system produces about 20 MWe when the plant is operated at its full nameplate thermal power rating of 62.5 MW. The plant is currently being used for testing of fuel behavior after cladding failure, demonstration of passive safety concepts and improved control systems, demonstration of a closed fuel cycle based upon an advanced metallic fuel design and as a test bed for advanced surveillance and diagnostic tools. Over 1000 signals from almost as many sensors are collected and routed to a data acquisition system (DAS) for monitoring and archiving purposes.

COMPENSATION FOR FAILURE OF CRITICAL SENSORS

In nuclear power plants, a multitude of signals generated from a wide variety of sensors are used for monitoring, control and safety functions. These signals represent various physical phenomena occurring in the system, many of which are closely inter-related and are essential for continued safe and economical operation. In addition, many of the sensors supplying critical information are difficult to maintain, repair or replace due to local hazardous environments, inconvenient locations or the need for system shutdown or operational disruption. If system operation is dependent upon the continued availability of certain sensors, the usual solutions are to use redundant sensors or to develop a maintenance program in which these sensors are periodically tested and if necessary, replaced or repaired. However, these approaches can increase the cost of the system due to the additional expenses related to the sensor redundancies or can have a negative impact upon the availability of the system due to the necessarily arbitrary maintenance schedule established in order to avoid forced outages due to critical sensor failures.

An alternative approach is to use a mathematical technique that can identify the relationships among all the signals at each operating state in order to generate "learned-states" of the system. Using such relationships developed from pattern-recognition algorithms, coupled with current observations of the state of the system, it should be possible to validate each signal as well as predict the expected value of any particular signal based upon the values of the other signals. Thus, this approach through its validation algorithms can identify the malfunction of any sensor and in addition, predict the expected value of the signal from that sensor that could be used in place of the actual physical signal to continue system operation until a convenient shutdown time is reached.

This section will describe such an approach and demonstrate its capabilities in the EBR-II reactor plant. This methodology can provide signal validation and estimation of the "true" signals from faulty sensors on a near real-time basis for hundreds of plant parameters. An experimental test will be presented of the capability of the SSA (System State Analyzer) code to provide accurate estimates of critical plant parameters following failures of the sensors that provide the signals used to determine these parameters.

Demonstration of Analytical Replacement of Faulted Sensors

The objective of the testing was to show that in a real-time operating mode, SSA could determine the "true" state of the reactor system based upon 11 previously learned operating states in the presence of multiple sensor faults as well as predict the values of signals in the presence of these simulated sensor failures and/or malfunctions. To accomplish this, the code was used in a learning mode to establish a learned-state matrix embodying information from 115 signals covering 11 separate operating states of the plant. Then, simulated failures in 15 individual signals were sequentially instituted through programming changes in the data acquisition system. The types of failures included sudden shifts in values as well as total loss of signal. As the signals were failed, the code was used in a real-time monitoring mode where all of the signals were estimated and compared with the actual plant measurements.

The test was conducted in two phases. The first phase focused on the ability of SSA to predict the value of the temperature rise across the core of the reactor (a critical parameter both in terms of operation and safety) when sensors contributing to this signal were abnormally operating. The second phase consisted of sequentially failing or faulting sensors (a total of 15 signals were affected) and observing the resulting capabilities of SSA to predict any or all signals in the state vector (115 signals).

The first phase of the testing was initiated with the reactor operating at steady-state at its normal full power condition. A learned domain was established using DAS data covering the previous 84 hours of operation at the same full power conditions. Then, while monitoring the SSA-predicted value of the reactor core temperature rise (whose "true" value is 180°F), this same signal was changed to read 170°F and held at this incorrect value for several minutes. This change was initiated at time -172 minutes in Fig. 1 which shows the measured signal (the boldest line) dropping off the bottom of the graph while the SSA-predicted value of this signal (the medium bold line) not changing from its normal fluctuating behavior. The pair of lighter lines on either side of the SSA-predicted curve are the upper and lower limits of the SSA-prediction and thus represent the uncertainty in the prediction. It can also be observed from this figure that the measured value of the signal from this sensor has been "de-validated", i.e., the sensor-based signal indicates a value that is not consistent with the "true" state of the system as indicated by the SSA-estimated signal. Thus, it is apparent that this signal is faulted in some way and should be investigated.

At time -164 minutes, this signal was reduced to read 0°F and held at this new value for several more minutes. As can be seen on Fig. 1 (although this additional change in the sensor occurs out of the range of this plot), SSA was able to continue to predict the expected value of this signal based upon the current state of the plant as provided by the other 114 unaffected signals. Thus, this phase of the test has shown that SSA is capable of accurately estimating the value of a signal even though the sensor directly generating this signal is malfunctioning or has failed.

The test was continued at time -156 minutes by restoring this DAS channel to its actual measured value of about 180°F so that all sensors were then operating properly. Then, at time -145 minutes, the DAS channel sensing average reactor inlet coolant temperature was changed from its normal value of 700°F to read 670°F. Since this signal is used as input to various calculations involving reactor power, reactor temperature rise and reactor flow rate, its simulated fault also affected 5 other signals. Thus, this single fault caused simulated malfunctions in a total of 6 signals. An illustration of the effect of the imposed fault in this DAS channel upon another related channel is shown in Fig. 2. In this figure, the reactor outlet flowrate (which is dependent upon the measured inlet temperature to determine the coolant density in order to convert the measured millivolt signal to gallons/minute, gpm) is shown, with the sensor-generated value shown in bold, the SSA-estimated value in medium and the uncertainty limits on the SSA-estimate in light. As can be seen, at -145 minutes when the simulated fault in the inlet temperature was initiated, the measured value of the flowrate shows an immediate spurious increase. However, since SSA has determined from the other signals in the plant that the true state of the system has not changed, the SSA-estimated value of the flowrate is essentially unaffected. An increase in the uncertainty bounds on the SSA-estimated value does occur, however, due to the increase in the uncertainty in determining the true state of the system since 6 signals are now reading "unusual" values, i.e., values that are not within the domain of learned states.

At -136 minutes, the measured value of the DAS channel for secondary system heat balance was changed from its normal value of about 62 MW to indicate 0 MW and at -129 minutes, the measured value of the DAS channel for IHX secondary outlet temperature was changed from its normal value of about 880°F to 800°F. Both of these signals, as well as the previously changed reactor inlet temperature, are used in the calculation of the reactor temperature rise as shown in Fig. 1 and which was the focus of the first phase of this test. Thus, 3 of the required input signals used to compute the value of the reactor temperature rise have been faulted and the resulting measured (actually calculated) value of this channel is shown in Fig. 1 for times greater than -136 minutes to decrease (off the scale of the graph) to about 132°F from its true value of 180°F. However, SSA has recognized that the true state of the system has not changed, even though 8 signals out of the 115 in the state vector are out of their learned domains, and the estimated value of the reactor temperature rise is basically unchanged and at its expected "true" value. Again, the uncertainty bounds on this estimation have increased due to the increased uncertainty in identifying the true system state.

The test was continued by sequentially faulting 7 additional channels starting at -121 minutes and ending at -80 minutes: superheater sodium outlet temperature was changed to read 400°F from its normal value of 785°F; superheater sodium outlet header temperature was changed to indicate 950°F rather than its true value of 794°F; evaporator sodium inlet temperature was changed to indicate 0°F rather than its true value of 787°F; evaporator sodium outlet temperature was changed to indicate 0°F rather than its true value of 593°F; steam header superheater outlet flow was changed to indicate 200,000 #/hr rather than its true value of 272,000 #/hr; secondary surge tank outlet temperature was changed to indicate 0°F rather than its true value of 591°F; and, finally, steam header superheater outlet temperature was changed to indicate 0°F rather than its true value of 817°F.

At this point in the test (at about -80 minutes), a total of 15 signals had simulated faults of various degrees. Yet, as can be seen from Fig. 1, SSA is still capable of recognizing the true state of the system from the remaining "normal" signals in the state vector and thus is able to make an accurate estimation of the true value of the reactor temperature rise as well as other system signals. For example, in Fig. 2 for the times between -121 and -70 when 15 signals were faulted, the estimated value of the outlet flowrate appears normal despite the erroneous measured value. Similarly, the SSA-estimated value of the reactor inlet temperature, as shown in Fig. 3, is shown to be essentially unchanged by these simulated failures including a fault in the sensor supplying the signal for this sensor. This result was typical of all other plant sensors included in the state vector.

The test was terminated at -56 minutes by restoring all channels to their normal readings.

Application of Technique to an Actual Sensor Failure

In addition to the controlled testing of this techniques capability to accurately estimate the correct value of a signal following or during simulated faulty operation of the sensor generating that signal, there have been a number of actual sensor failures or malfunctions in the EBR-II plant during periods that the SSA was being used for routine surveillance. In one such instance, a thermocouple that was used to indicate the reactor coolant temperature rise across the core (not the same one as discussed previously in this paper) exhibited degraded performance. As can be seen from Fig. 4, which shows the SSA-estimated value of the signal value (with estimation uncertainty bands) and the thermocouple-generated signal, degradation appeared to begin at about -216 minutes. At times greater than -216 minutes, the SSA-estimated value increases slightly while the sensor-based value decreases. The increase in the estimated value was later traced to the actions of the reactor operator who increased reactor power slightly to compensate for what he thought was a drop in reactor temperature rise based upon this sensor. The SSA-estimated value responded appropriately to this action following the real change in the plant state, while the degraded sensor-based signal did not.

The thermocouple sensor, although appearing to recover at about -30 minutes, subsequently degraded further and is assumed to have failed. For the remainder of that reactor run, the indicated sensor-based temperature rise across the core remained at about 83°C (150°F), while the SSA continued to estimate the temperature rise to be about 100°C (180°F). The core temperature rise measured and calculated from other plant sensors during that time was within one degree of the SSA-estimated value. This event and its subsequent evaluation has demonstrated the value of this technique in signal estimation as well as its contribution to plant control, providing the operator with additional information that can be utilized to determine the proper response to apparent changes in the plant operating state.

SURVEILLANCE AND FAULT DETECTION/DIAGNOSIS OF PLANT SYSTEMS

In order to reliably and safely operate a nuclear power plant, it is necessary to continuously monitor the performance of numerous subsystems to confirm that the plant state is within its prescribed limits. An important function of a properly designed monitoring system is the detection of incipient faults in all subsystems (with the avoidance of false alarms) coupled with an information system that provides the operators with fault diagnosis, prognosis of fault progression and recommended (either automatic or prescriptive) corrective action. In this section, such a system is described that has been applied to reactor coolant pumps. This system includes a sensitive pattern-recognition technique based upon the sequential probability ratio test (SPRT) that detects incipient faults from validated signals, an expert system embodying knowledge bases on pump and sensor performance, extensive hypertext files containing operating and emergency procedures as well as pump and sensor information and a graphical interface providing the operator with easily perceived information on the location and character of the fault as well as recommended corrective action. This system is in the prototype stage and is currently being validated utilizing data from a liquid-metal cooled fast reactor (EBR-II).

Since it is essential that only validated data be sent to any diagnostic program and also that alarms should be detected early and not be missed or falsely indicated, it was felt that the use of nominal, smoothed sensor data with high/low limit tests was inadequate and could not be directly used. Thus, a technique was adapted from an extremely sensitive statistical test, the sequential probability ratio test (SPRT), that examines the noise characteristics on signals from identical pairs of sensors deployed for redundant readings of continuous physical processes from a particular subsystem or component. The comparative analysis of the noise characteristics of a pair of signals as opposed to their mean values permits an early identification of a disturbance prior to significant (grossly observable) changes in the operating state of the process. For example, a change in the skewness, bias or variance of the signals can be detected by the SPRT and used to initiate the automatic diagnostic program and annunciated to the operators. The use of two or more identical sensors also permits the validation of these sensors, i.e., determines if the indicated disturbance is due to a change in the physical process or to a fault in either of the sensors.

In addition, it is desired to permit the operators to focus on the current problem and not to overwhelm them with large amounts of data. This leads to the use of an embedded expert diagnostic system that embodies operational experience of the relevant physical processes and sensors. Once a disturbance is indicated, the expert system reads in the pertinent data from the DAS (after validation by SPRT), performs a diagnosis of the fault, and after informing the operator of the problem, offers prescriptive actions as well as direct access to the proper operational procedures through the use of hypertext files.

Overview of the SPRT Technique

A brief overview of the theoretical basis of the SPRT technique will be described in this section. The basic approach taken is to analyze successive observations of a discrete physical process by a comparison of the stochastic components of the signals generated by similar sensors monitoring the process. If Y_k represents a discretized difference sample from two sensors at time T_k, the set of values $\{Y_k\}$ should be normally distributed with a mean of zero if the system is operating normally and the sensors are functioning within their specifications. Note that if the two signals being compared have different nominal means (due, for example, to differences in calibration), then the input signals will be pre-normalized to the same nominal means during initial operation.

The goal of the sequential measurement of Y_k is to declare that the system is degraded if the set $\{Y_k\}$ exhibits a non-zero mean, e.g., a mean of either +M or -M, where M is a pre-assigned system disturbance magnitude. The problem is to decide between two hypotheses: H_1, the set $\{Y_k\}$ forms a Gaussian[1] probability density function with mean M and variance σ^2; or H_2, the set $\{Y_k\}$ forms a Gaussian probability density function with mean 0 and variance σ^2. The SPRT technique provides a quantitative framework that permits a decision to be made between these two hypotheses (for both the physical process and the sensors) with specified (input) misidentification probabilities. Specifically, the user must input an acceptable false alarm probability (α, the probability of accepting H_1 when H_2 is true) and missed alarm probability (β, the probability of accepting H_2 when H_1 is true). Utilizing these input values, it can be mathematically demonstrated that a decision strategy can be based upon the comparison of a statistical quantity developed in Reference 1 (based upon a sequential measurement and comparison of the values Y_k and defined here just as S) with a function of α and β as follows:

if $S < \ln(\beta/(1-\alpha))$,	accept H_2;
if $\ln(\beta/(1-\alpha)) < S < \ln((1-\beta)/\alpha)$,	continue sampling;
if $S > \ln((1-\beta)/\alpha)$,	accept H_1

The value S is sequentially computed at each discrete time interval that a value Y_k is determined and its value is monitored within the program relative to the above criteria in order to determine whether or not an alarm should be annunciated and the expert diagnostic system automatically initiated.

It can be theoretically shown that a decision test using the SPRT method has an optimal property; that is, for given probabilities α and β there is no other possible procedure with lower error probabilities or expected risk and with shorter length average sampling time than the SPRT. It is because of this property of the SPRT and its inherent simplicity that it was chosen as the disturbance detection tool for this monitoring and diagnostic system.

Description and Operation of Diagnostic System

An overview of the diagnostic system is shown in Fig. 5. As indicated earlier, although the system has been developed in a generalized manner so as to perform monitoring and diagnostic tasks of any system, the current prototype has been restricted to reactor coolant pumps. The basic data utilized by the system include the signals generated by seven sensors attached to each of two pumps. These sensors measure the pump impeller rotational speed (with three redundant tachometers), the vibration of the pump housing (with two redundant accelerometers), the electrical power drawn by the pump and the coolant discharge pressure from the pump. These signals are sent to the DAS from the sensors where they are converted into engineering units and then fed into the artificial-intelligence-based inference engine and finally to the display media in the reactor control room.

The diagnostic system (referred to in Fig. 5 as the AI inference engine) consists of several modules written in the C programming language and linked together in a structure that permits unidirectional goal-driven logic as well as recursive searching. Its overall architecture is shown in Fig. 6 where it is seen that the user interfaces with the system are provided only at the front-end (simply to initiate the system and to identify the particular sub-system to be monitored) and at the back-end (where the diagnosis, prognosis and corrective action(s) are provided as well as access to explanations, procedures, etc.).

Once initiated through the front-end driver, the system actuates the fault-detection system which has a buffered interface with the plant data acquisition system. The digitized signals from the specified sub-system (the reactor coolant pump in the present application) are read into computer memory from the DAS and passed through a logic structure incorporating the SPRT technique. Essentially, the algorithms in this structure perform the SPRT analysis on each pair of sensors, determining if any degradation is present. If all sensors show normal, then the time step is incremented, a new set of data from the DAS is read, and the process repeats with a passive notice appearing on the monitor indicating that the system is operating normally. However, if degradation of a signal is observed, the particular sensors are first validated; if they fail the validation, a sensor fault is declared and control passed to the sensor diagnostic system. If all the sensors are validated, then a fault in the pump operation is declared and control passed to the pump diagnostic system. Once the pump or sensor diagnostic systems complete their assessment of the fault, the resulting information is passed to the operator through a display on the monitor and a complete report of the event recorded in a file on hard disk for future reference.

The pump and sensor diagnostic systems were both developed using a commercial expert shell having a capability of embedment within a larger code structure written in the C language, an ability to utilize both shallow and deep knowledge within and linked to the shell, linking exterior data bases to the final system and inclusion of hypertext features.

The user initiates the system through a front-end graphic-interfaced driver system where choices are made relative to which plant subsystems or components are wished to be monitored. At the present time, only the reactor coolant pumps in the primary pumping system are implemented. Once initiated, data from the pre-selected sensors (the particular choice of sensors is made internally based upon the user selection of the subsystem to be checked) are read from the plant DAS for continual processing and surveillance. Due to the stringent configuration and function control placed on the DAS of a nuclear power plant, it is necessary to buffer the system from the DAS resulting in an effectively read-only access to the plant data.

The signals from the selected sensors are passed through a net utilizing the SPRT algorithms searching for either sensor or process disturbances. If normal operation is confirmed, a notice is generated on the monitor screen to indicate that the pumps are within their normal operating state and then a new set of data are read and the search for disturbances repeated. This internal iterative looping is continued until either the operator terminates the diagnostic system operation or a fault is detected. If a fault is detected, the SPRT-based algorithms then identify the source of the fault, i.e., a sensor malfunction or a disturbance in the physical process (pump operation). Based upon this determination, control is then passed to either the pump or the sensor diagnostic program. In addition, the data that will be needed for the final diagnosis are generated (additional data may be read from DAS and existing data converted into the format needed for subsequent handling) and written to a separate file for access by the downstream programs.

If the disturbance was identified by the SPRT algorithms as originating in one of the sensors, an expert diagnostic system specific to that sensor is activated. This system initiates a search for the root cause of the disturbance in the identified sensor by a combination of forward and backward chaining in the rule-based logic structure accompanied by data input read from the file(s) generated in the fault detection/sensor validation phase as well as execution of mathematical models (in external codes) of the sensor behavior. Typical faults searched for by this system include signal drift, change in signal bias (offset), increased stochastic content in signal, complete or partial loss of signal, etc.

It was necessary to develop a separate knowledge base and expert system for each sensor type since the dynamics and failure modes of the diverse types of sensors involved precluded a generalized and unified approach. Of course, conditional branches leading to individualized knowledge bases contained within a single system could have been utilized, but the approach taken results in a more flexible system relative to its amenability to upgrading and transferring to other applications.

If all of the sensors were validated, i.e., confirmed as operating within their normal specifications, and a disturbance was indicated to exist in the physical process (pump), then the expert diagnostic system for the pumping system is initiated. This system operates similarly to those used for the sensors, but includes not only information on the pump itself, but other plant parameters that are affected by or contribute to the operation of the pump. Since the EBR-II plant has two reactor coolant pumps that provide flow through independent piping systems that ultimately merge in a mixing plenum, it is necessary to include a considerable amount of information on the hydraulic characteristics of this plant system in order to interpret the measured data relative to potential faults. This can be accomplished either by a detailed mathematical model of the hydraulic circuit including the pumps, or through an extensive set of "if-then" rules. The approach taken here was a combination of these, where a simplified thermal-hydraulic model was used in conjunction with a shortened list of rules.

Once either of the expert diagnostic systems reaches a conclusion as to the cause of the disturbance, the operator is immediately notified through an annunciated message on the monitor screen and a detailed report is written in a file on the hard disk for future reference. Through a graphically-displayed screen message, the operator is also informed of the exact problem, its cause, recommended corrective action and is offered the option of requesting an explanation of the logic and information used by the system to arrive at its conclusions. In addition, the operator can directly access the appropriate operating or emergency procedures or system design descriptions of the affected sensor or pump. Since these documents have been largely converted to a hypertext format, the pertinent sections of the documents (as well as specific key words or phrases within the documents) can be immediately accessed by the firing of rules related to the identified fault or by manual action of the operator at the keyboard.

Example Application Using EBR-II Plant Data

In March, 1987, EBR-II experienced a pump-degradation event in one of the two primary coolant pumps that pump liquid sodium through the reactor core. The event was caused by mechanical binding of the rotating shaft, which reduced the flowrate of coolant through the core, triggering an automatic scram of the reactor. Mechanical torquing of the pump shaft during the shutdown was sufficient to clear the sodium-oxide debris that caused the binding, and the reactor was returned to operation.

Archive data were retrieved from the actual pump-degradation event that occurred in order to test the capability of SPRT to detect this fault. Figure 7 shows the results of applying the SPRT technique to the data recorded during the binding event. Pump power signals were used as input to the SPRT algorithm in this example. The difference function, Y, plotted in the third subplot in Fig. 7 represents the difference between pump 1 and pump 2 powers, after normalizing the power to a common nominal value.

The bottom subplot in Fig. 7 shows the computed value of the SPRT index. The significance of the SPRT index is: If both signals are following the same physical processes with similar noise patterns, the SPRT index is a negative number. In this case the index is continuously reset to zero. If the statistical quality of either signal begins to change, which may result from sensor degradation or from a disturbance in one of the pumps, then the SPRT index is driven positive at a rate that increases with the degree of degradation. If the SPRT index reaches the upper threshold of 4.6, then one can conclude with a confidence factor of 99% that the two signals are no longer governed by the same probability density function. At this point the status of a warning flag is set, the SPRT index is reset to zero, and the calculations continue.

From the lower plot in Fig. 7 it can be seen that by the time pump 1 power started increasing the SPRT was continuously exceeding the negative threshold (diamond symbols at 4.60). The interesting feature that emerges from the plot is that several minutes before there was a discernible increase in pump power, the SPRT was indicating "data-disturbance" warnings. It can be concluded that at the time the data recording was initiated, the statistical quality of the pump 1 parameter was already significantly different (at the 99% confidence level) than pump 2.

CONCLUSIONS

The pattern-recognition techniques embodied by the SSA and SPRT continue to be exploited for use in the EBR-II plant-life extension work and in other applications. The SSA is being applied at EBR-II in several specific areas related to plant-life extension. One application is the substitution of the on-line SSA calculated estimate of the temperature rise of the primary coolant across the reactor core to replace the signal from a failed, inaccessible thermocouple in the reactor outlet pipe. Because much of the originally installed primary system instrumentation has failed and is inaccessible for replacement the capability to replace key parameter sensor signals with validated calculated signal values is important to continued long-term availability of EBR-II. The other application is the use of the SSA along with SPRT for long-term degradation momitoring of the EBR-II primary pumps which are critical to extended-life operation of EBR-II.

Although these applications are in their early stages, the initial results together with the results of other SSA and SPRT application at EBR-II, have indicated that pattern-recognition techniques can be very useful in plant diagnostics and surveillance to support different aspects of a plant-life extension program.

REFERENCES

1. R. W. King, "An Integrated Plant-life Extension Program for EBR-II," Proceedings of the ANS International Topical Meeting on Operational of

Nuclear Power Systems in Normal and Adverse Environments in Normal and Adverse Environments, pp. 706-711 (1989).

2. J. Mott, R. Young, and R. King, "Pattern-recognition Software for Plant Surveillance," Proceedings of the American Power Conference, Chicago, Illinois (1986).

3. R. King, W. Radtke and J. Mott, "Pattern-Recognition System Application to EBR-II Plant-Life Extension", Proc. Nuclear Power Plant Life Extension, Snowbird, Utah, USA, 31 July-3 August 1988, Volume II, pp. 512-518.

4. K. Gross and R. Singer, "Automated Surveillance of Reactor Coolant Pump Performance", Proc. Fourth Intl. Workshop on Main Coolant Pumps, Phoenix, AZ, USA, 16-19 April 1991.

5. R. Singer, K. Gross, K. Humenik, and M. Walsh, "Reactor Coolant Pump Monitoring and Diagnostic System", Proc. 2nd Intl. Machinery Monitoring and Diagnostics Corp., Los Angeles, CA, USA (1990) pp. 19-24.

6. W. Lehto and K. Gross, "Expert System Applications in Support of System Diagnostics and Prognostics at EBR-II", Proc. US-Korea Seminar on Applications of Expert Systems to Power Systems and Industries, Seoul, Korea, 14-18 August 1989.

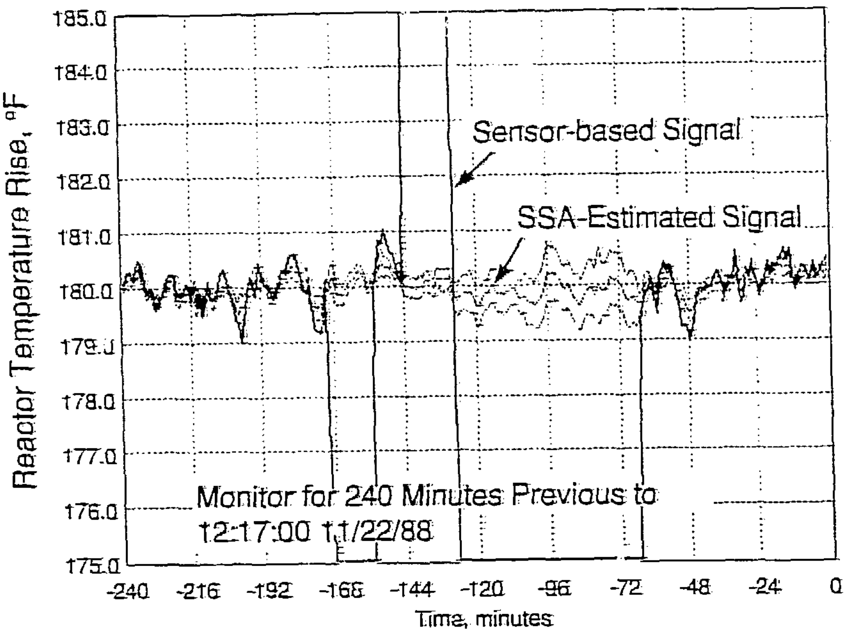

Figure 1: Estimated Core Temperature Rise with Sensor Failures.

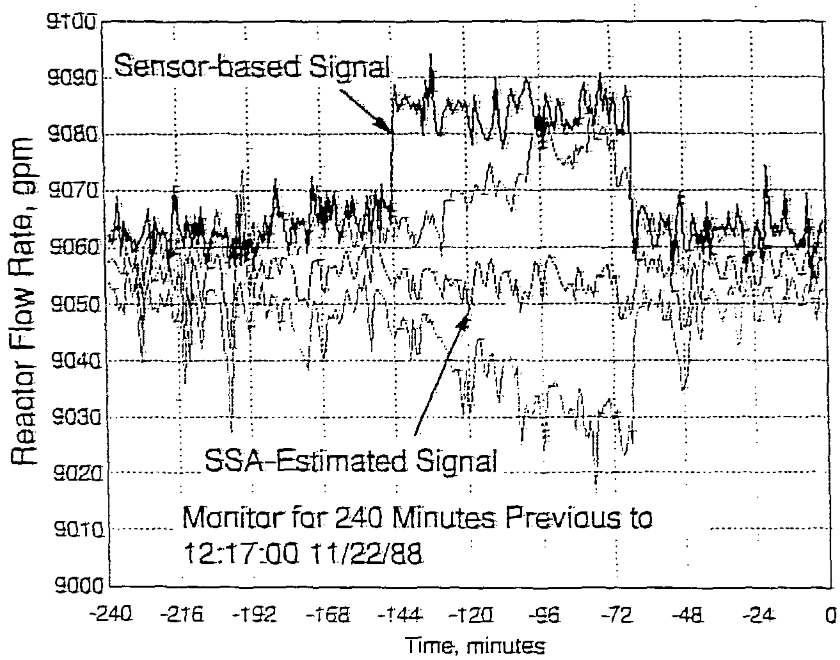

Figure 2: Estimated Reactor Flow Rate with Sensor Failures.

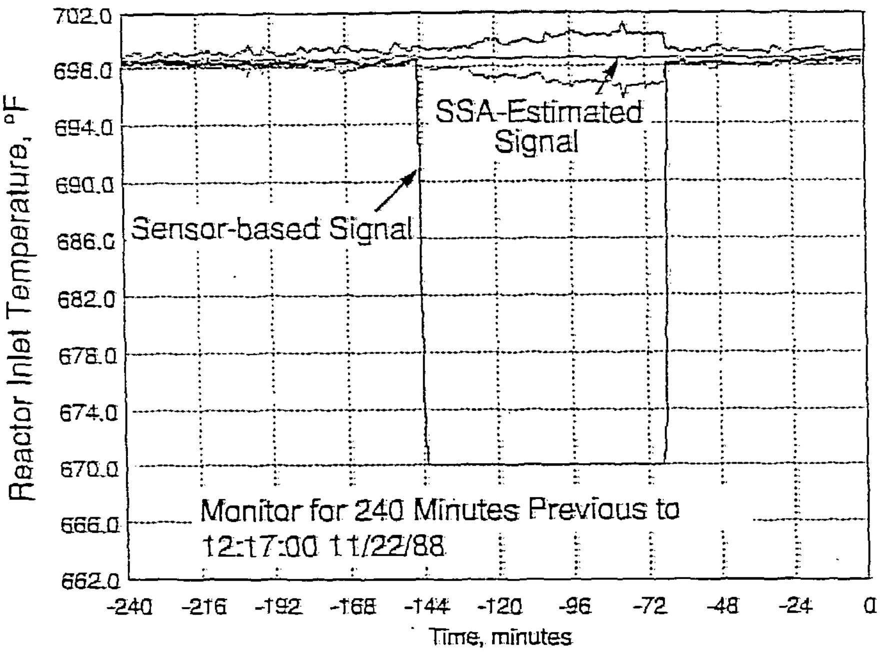

Figure 3: Estimated Reactor Inlet Temperature with Failed Sensors.

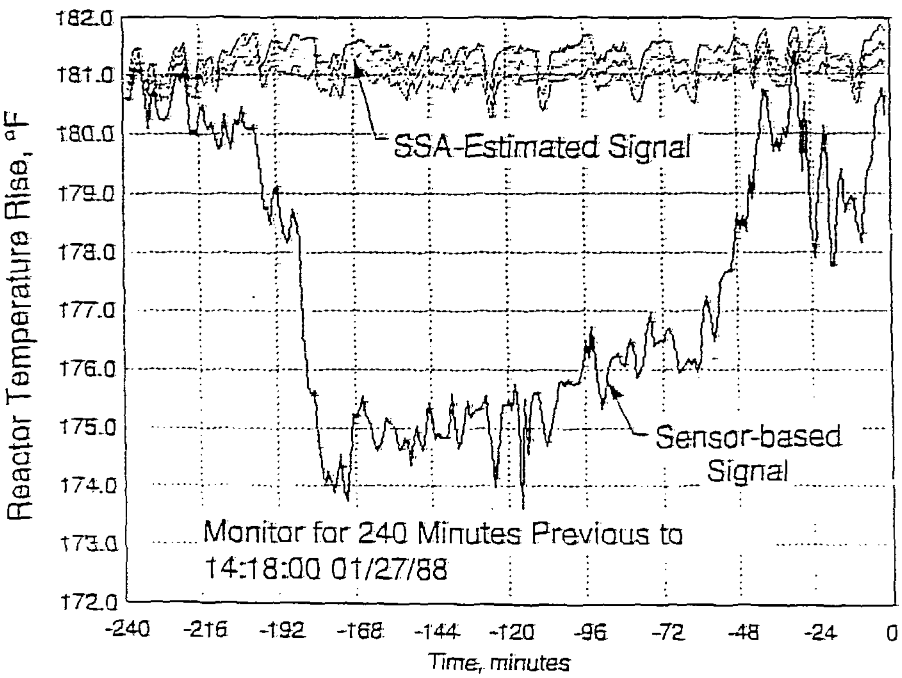

Figure 4: Detection of a Fault in the Sensor-based Signal for the EBR-II Core Temperature Rise.

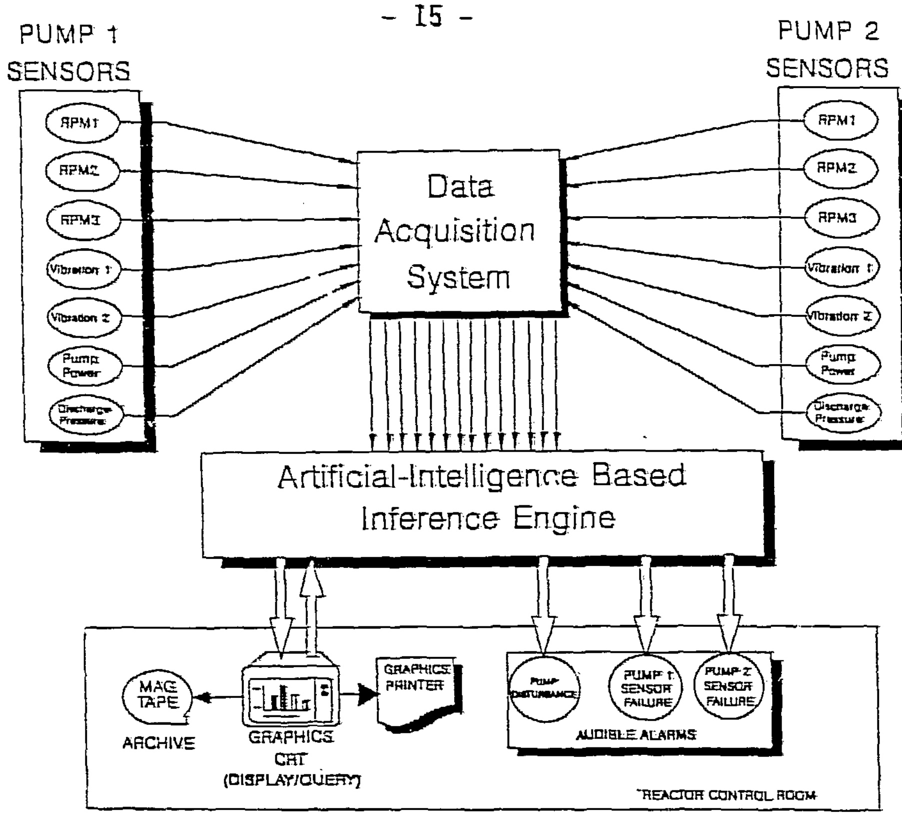

Figure 5: General Layout of Reactor Coolant Pump Monitoring and Diagnostic System.

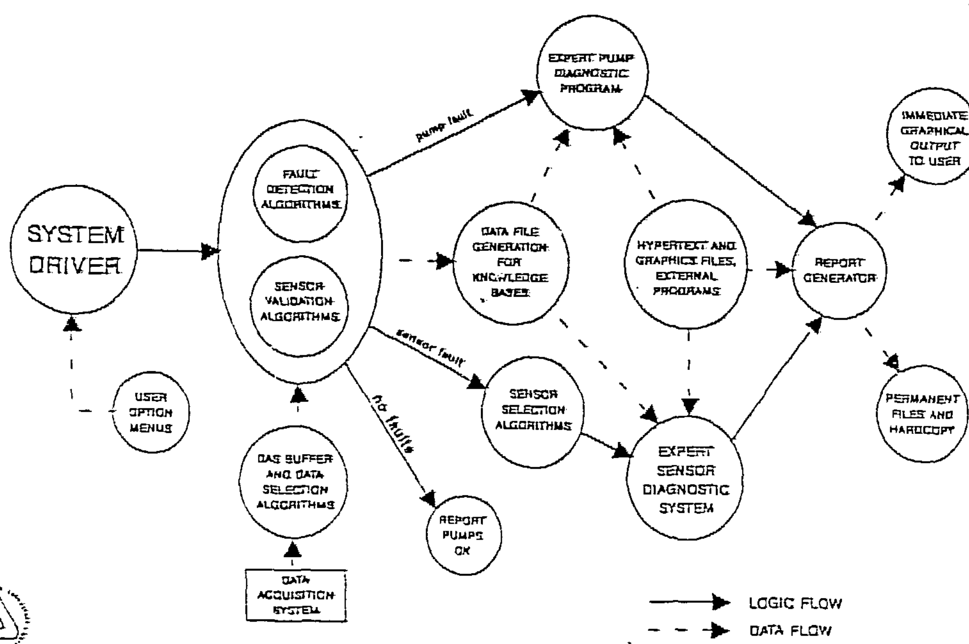

Figure 6: Detailed Structure of SPRT-based Reactor Coolant Pump Monitoring and Diagnostic System.

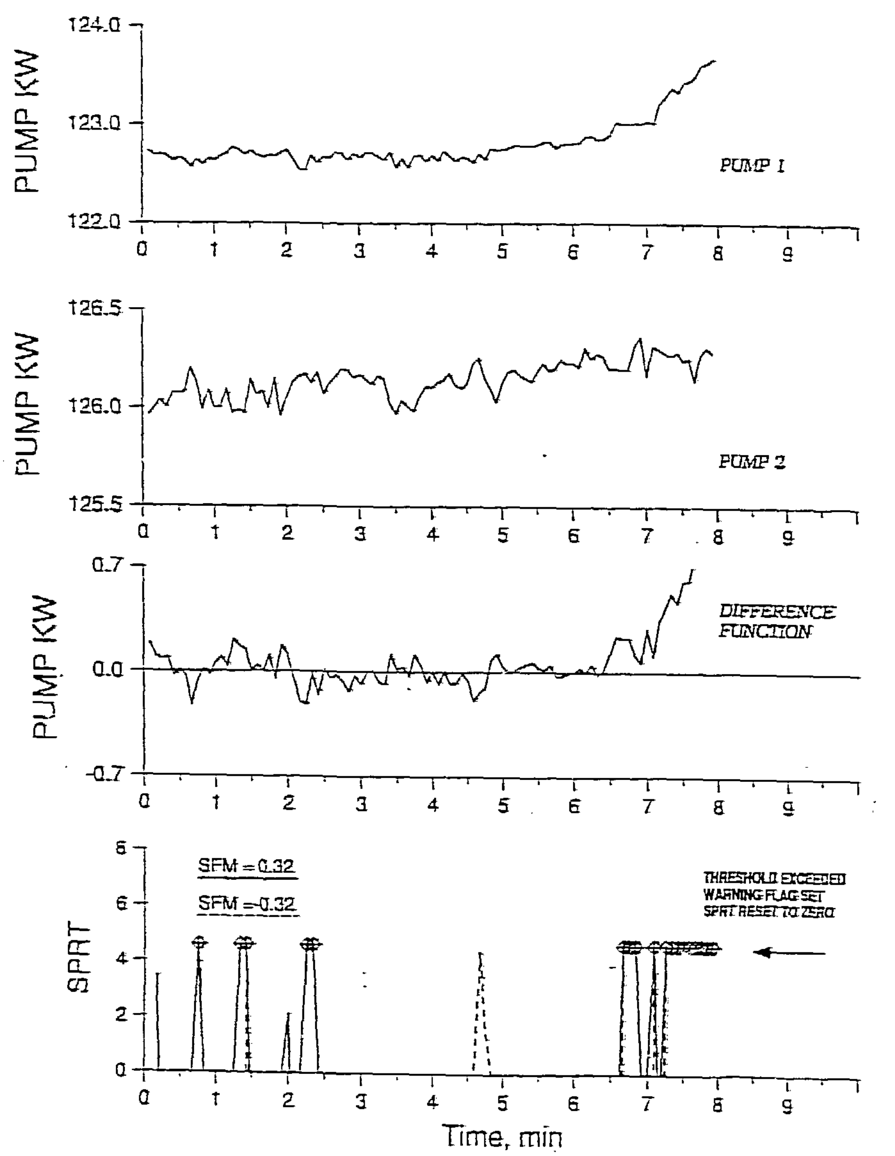

Figure 7: Illustration of Pump Fault Detected by the SPRT Monitoring System.