Instrumentation Surveillance at TMI 1 Using Pattern Recognition Techniques

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ABSTRACT

Pattern recognition software is being used at GPU's Three Mile Island Unit 1 generating station to assist engineers and technicians in monitoring 540 plant instruments. A goal of this project is to detect unusual instrumentation behavior, including drift, before serious problems develop. The software has detected small amounts of drift that did not exceed weekly surveillance check criteria, and which were corrected at the next Technical Specifications required calibration. A pressurizer spray valve that did not reseat correctly after routine testing was also detected. This paper discusses the instrumentation monitoring program, the methods used to determine situations needing further investigation, and results of the monitoring effort.

INTRODUCTION

The need to monitor the condition of many signals in an operating power plant has driven the development of computer aided methods to automate this process. A successful computerized data validation tool must be easily maintainable, not prone to calculational failure, and tolerant of faulty measurements. The pattern recognition software discussed in this paper is one tool that satisfies all these requirements.

The pattern recognition data validation process used at GPU is analogous to the process an experienced operator goes through in monitoring the measurements displayed in the control room. The operator consciously or subconsciously organizes signals into related groups. As the plant operates over the load range, patterns or relationships among the observed groups of measurements are learned as reference values. When new measured values are observed, a mental comparison is made to the reference values to see whether the new data "fits" a known pattern. Measurements that do not fit are identified for further scrutiny. An example of a pattern is at 100% load, all extraction pressures should increase going up the feedwater line, and each value should be approximately X psi. The pattern recognition software tool follows the same sequence using a computer instead of the human mind for "learning" reference patterns and comparing them to current values.

To improve the detection of drifting instruments, failed instruments, and deteriorating equipment, GPU chose pattern recognition software to assist their engineers. GPU engineers monitor the signals from 540 instruments with values recorded every four hours. The analysis of these 22,680 values is performed by one engineer in about four hours per week with the aid of the method described in this paper. To accomplish the same task manually, an engineer would have to examine 567 signal values every hour for 40 hours per week.

In the results section of this paper, two different data sets are presented. Each data set contains a signal that deviated from its predicted value and was shown to have undergone a change that was corroborated by further investigation. Neither measurement deviation posed a problem for the plant, but the corroboration of the deviations detected using this tool verifies its usefulness in a plant setting.

DATA ORGANIZATION

The first task in pattern recognition data validation was to group instrument signals whose values constitute a pattern indicative of the condition of a plant subsystem. The term **"data set"** was coined to mean a group of related signals and the data files associated with a pattern recognition analysis. A snapshot of data containing one value for each measurement in the group at one point in time, is called a **"state."**

After signals were grouped, the next step was to build a **"reference library"** for each group. Each library contained several data states (snapshots) that included patterns of measured values covering the operating range of the process. At GPU, the data for the reference libraries were collected just after an outage, when the instruments had recently been calibrated and the plant was known to be in good operating condition. Every signal value in each state was examined by the engineers before it was included in a reference library. Data not representative of good, well-calibrated measurements was excluded from the reference library.

Weekly data analysis of changes in calibration, recalibration, or replacement of instruments during the following operating cycle resulted in adding states to existing libraries and in the creation of new libraries. Libraries were expanded only after it was verified that a new condition existed and it was shown that the new condition was stable. Reference libraries were sorted, examined, and edited with graphical tools to add or remove appropriate data sets and to ensure that the result was a comprehensive library of good data. The reference library is the computer counterpart to the experienced operator's memory of "what the measurements should be".

The term "good operating data" is defined to mean values that reflect measurements from the plant in the operating modes that actually occur. These data did not reflect "perfect" operation or the most efficient operation; they were merely representative of routine plant operation.

DATA GATHERING

At GPU, data to be validated are downloaded every four hours from the plant computer to the LAN fileserver, and are then downloaded weekly to a 486/33 PC for analysis. A special program was written to permit the engineers to create data files grouped by system or monitored equipment and to provide the PC data in a format compatible with the pattern recognition tool, either in ASCII or binary format. The program also permits adding or deleting a computer point (signal) from a file. File size ranges from four (4) to fifty (50) signals. No manual data entry is required except for signals that are not available on the plant computer.

Data sets that are being analyzed weekly include temperature, level, pressure, vibration, and flow measurements of:

- reactor building spray tanks,
- condensate pump and condensate booster pumps and motors,
- circulating water pumps and motors,
- main and auxiliary condensers,
- feedwater pumps and turbines,
- heater drain pumps and motors,
- integrated control system,
- makeup pumps and motors,
- makeup system,
- secondary plant system,
- reactor building conditions,
- reactor building tanks and sumps,
- reactor coolant system,
- reactor coolant pumps,
- steam generators,
- main generator support systems,
- turbine bearings,
- main and auxiliary vacuum pumps and motors, and
- emergency diesel generators.

SOLUTION METHOD

The solution method is analogous to the experienced operator's mental process of deciding whether the current data fit known patterns. Each data set is analyzed as an entity with measured and predicted values for each signal tracked individually. A data set analysis results in a predicted value and a quality flag for each measurement in the set, and a validity flag for the monitored state.

The pattern recognition software uses a function called "overlap" to assign a single value that rates the similarity of any two states of data. This function is part of a matrix manipulation process used to predict the data for a monitored state and to determine measured data quality. The overlap is always a value between 0 and 1.0, with 1.0 indicating that two states are identical.

The solution algorithm begins by determining the overlap of the current state with every state in the reference library and sorting the reference library states in order of most similar to least similar. A subset of the most similar states from the reference library is then chosen for further use. This selection algorithm bounds each of the current measurements to the extent possible. An essential feature of this method is that it maximizes similarity between the current state and the reference library states rather than minimizing differences between them. If a measurement in the current state cannot be bounded by values in the reference library, that signal has very little influence on the predicted values. Studies (1) have shown that over 20% of the measured signals can be failed without significantly affecting the quality of the predictions.

The selected states are used to build a matrix model of the system and produce a prediction for each measurement in the current state. This function of the model building process is similar to the "learning" process used by neural networks; however, it occurs in about three seconds on a 386/16 PC and never fails to produce a prediction for each signal in the current state. Neural networks can take hours to "learn," and occasionally, they fail to arrive at a solution.

Two levels of comparison are made between the predicted and current values. At the top level, the predicted state of values is overlapped with the current state (measured values) to calculate one number that determines if the current state is "within the reference library." If the overlap exceeds a validation parameter that is characteristic of a given system, there is high confidence that the predicted values are accurate. This is analogous to an operator deciding that the process is operating in an expected manner.

The second level compares the predicted value for each signal in the state to its corresponding measured value. The magnitude of this difference is compared to the calculated deviations for each signal. In these analyses, a calculated deviation is defined as one minus the overlap for the two states times the predicted value. If the difference is greater than three calculated deviations, then the current measured value is flagged as bad. This is analogous to an operator deciding that a measurement looks wrong.

RESULTS

Figure 1 is a trend of steam generator level measured and predicted values between December 26, 1991, and February 5, 1992. The steam generator level measurement identified by tag name LT-776 abruptly dropped from 243 to 240 inches. This change occurred between 124 and 128 time periods before the most recent state on the plot (between January 6 and 7, 1992). The solid black lower X-axis indicates the times when the predicted and measured values differed by more than three calculated deviations and the measured value was flagged bad. Although not shown in Figure 1, a "select line" feature of the software can be activated by pressing the arrow keys on the keyboard and moving the cursor to point to a specific portion of the plot. The select line is used to show the date and exact values for any set of data.

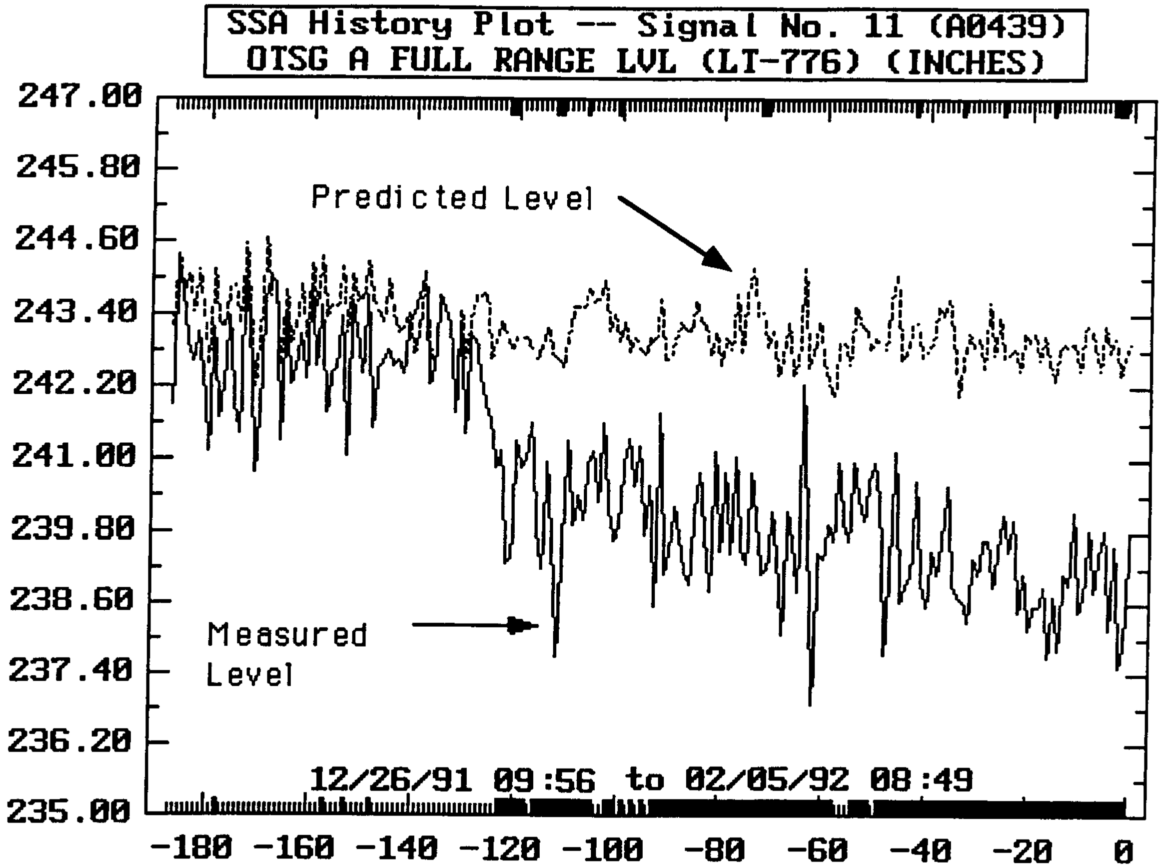

Figure 1. History Plot of Measured and Predicted Steam Generator Level.

None of the other steam generator level measurements showed a similar change, and all measurements still agreed within the weekly surveillance check requirement of +/-20 inches. Therefore, it was not necessary to initiate a Technical Specifications calibration, and no immediate action was taken. The instrument was watched carefully for the rest of the year, and no other unusual changes were noted. In December 1992 a regularly scheduled Technical Specifications calibration was performed, and the measurement recovered the 3 inch level in its reading. No specific reason for the instrument drift was determined.

A single keystroke is used to bring up a bullseye plot of the steam generator level data set shown in Figure 2. This figure

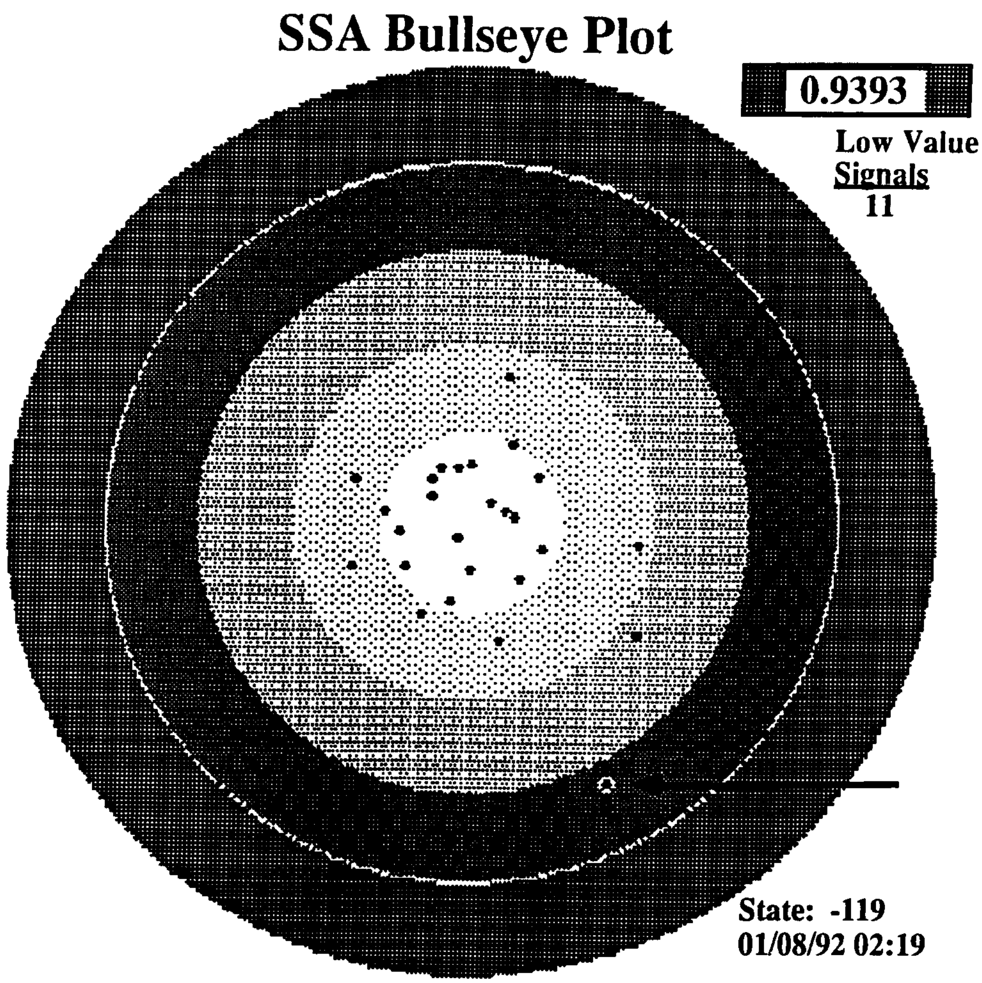

Figure 2. Bullseye Plot Showing the Steam Generator Level (Signal 11) Flagged Bad.

contains information about each system measurement at one instant in time. Each concentric ring represents one calculated deviation for the measured signals. The measurements for predicted and current values that differ by more than three calculated deviations lie outside the third circle. These points are listed on the left of the figure for high measurements and would be on the right of the figure for low measurements. Signal 11, indicated by the arrow, is more than three calculated deviations lower than its predicted value and is listed as a low value bad signal.

The overlap of the predicted and current state is shown in the upper right hand corner of Figure 2. On a color display, this value would be surrounded by a green box for a current state lying within the reference library and a red box when the current state is not within the reference library. For this analysis, the current state is within the reference library, and the validation results are accurate. The time at which the analyzed data was gathered is shown in the lower right of the figure.

Again, a single keystroke is used to present the data in a format called a signature plot which is shown in Figure 3. This signature plot has one vertical bar for each signal. The length of the bar represents the number of calculated deviations that the predicted and current signal values differ. The light shaded bars represent signals that differ by less than two calculated deviations between measured and predicted values. The medium dark bars represent signals that differ by two to three calculated deviations, and the black bars represent signals that differ by more than three calculated deviations. The signals with large deviations are identified on the sides of the plots. The overlap of the predicted and current state is again shown in the upper right hand corner.

A separate analysis of a data set containing pressurizer measurements detected a high spray line temperature (RC11-TE) as

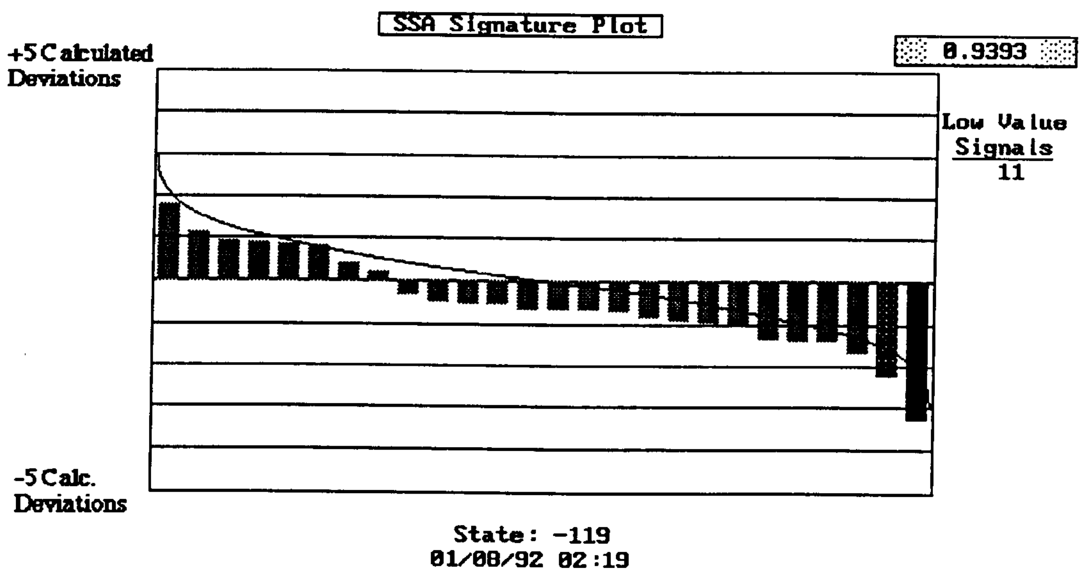

Figure 3. Signature Plot Showing Steam Generator Level (Signal 11) Flagged Bad.

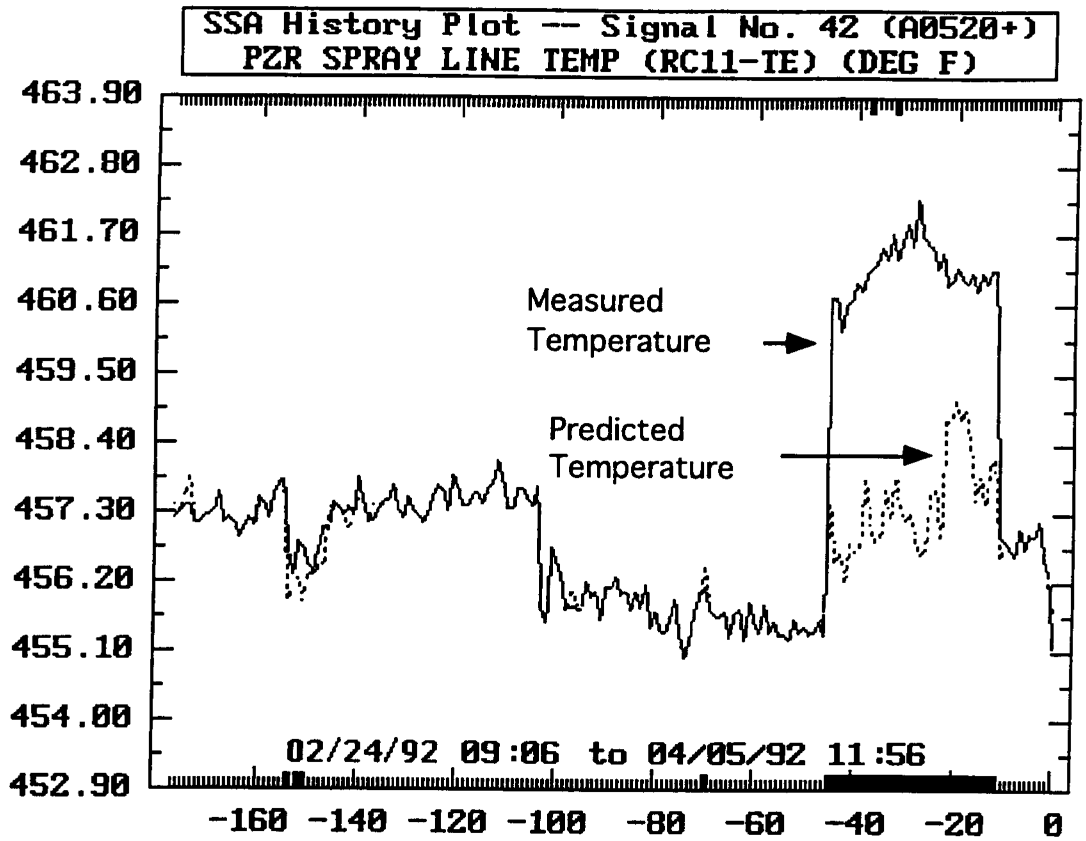

Figure 4. History Plot Showing Pressurizer Spray Line Deviating Above Predicted Value.

shown in the history plot in Figure 4. The temperature was flagged bad at -45 on the X-axis (45 time periods before 04/05/92, or on March 23). The temperature returned to normal where the X-axis turns from solid black to white on March 30 (-11 on the X-axis).

Subsequent investigation uncovered the following scenario. During a normal surveillance of pressurizer spray line valves, the normally open valve is closed, the normally closed valve is opened and then closed, and finally the normally open valve is opened. This routine surveillance was done late on March 29. After the pattern recognition analysis was performed on April 3, a question was raised about the increased temperature in the pressurizer spray line. This increase suggested that the valve did not fully reseat. Within a few hours, the valves were cycled again, and the temperature returned to normal and stayed normal, suggesting proper valve reseating.

Figure 5 presents a bullseye plot of the pressurizer data set shortly after the spray line valve test. It shows that only one measurement in the data set significantly differed from its predicted value. The overlap of predicted state and current state is 0.9807, indicating that the data in the current state are well within the reference library and that the validation results are accurate.

The signature plot shown in Figure 6 more dramatically presents the information in Figure 5. The long black bar on the left of the scale shows that signal 42 (the spray line temperature) is well above its predicted value.

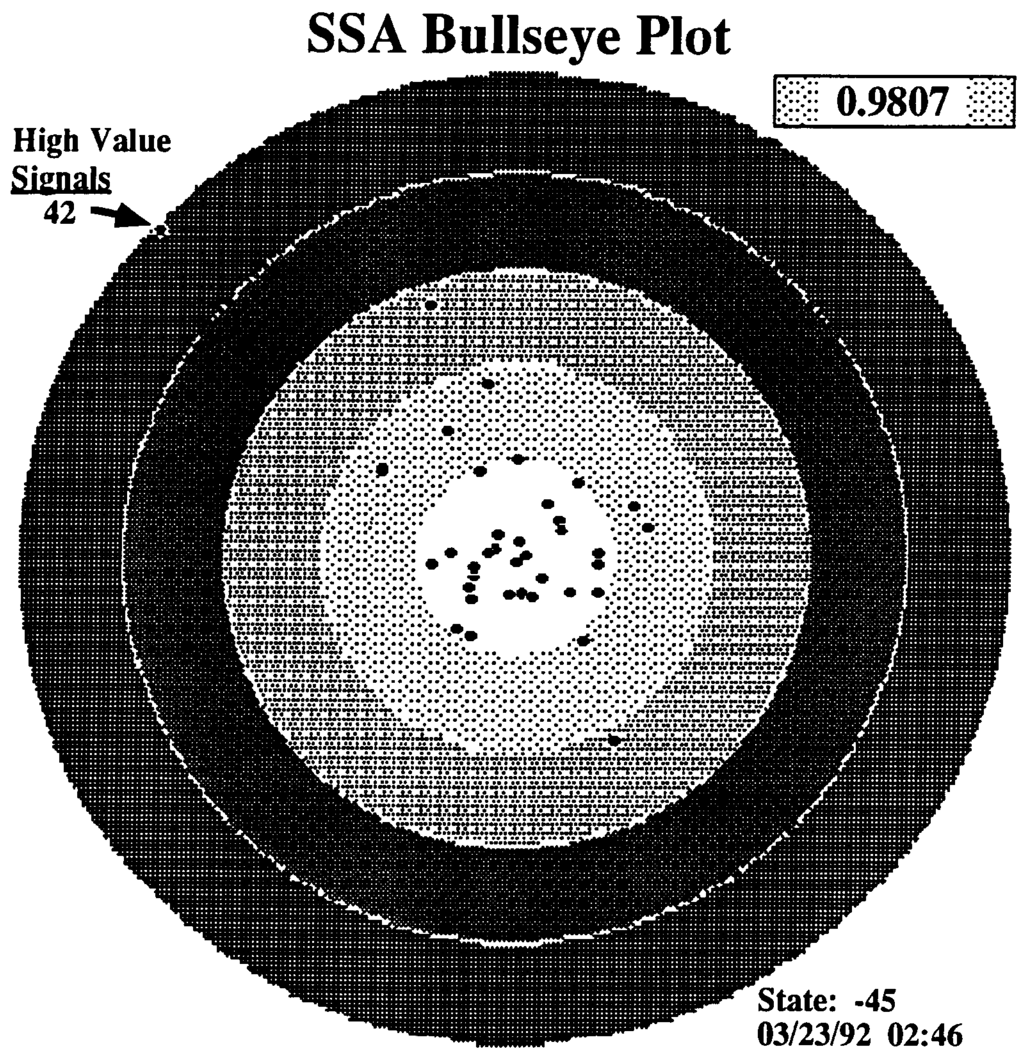

Figure 5. Bullseye Plot Showing Analysis Results Just After Pressurizer Spray Line Valve Test.

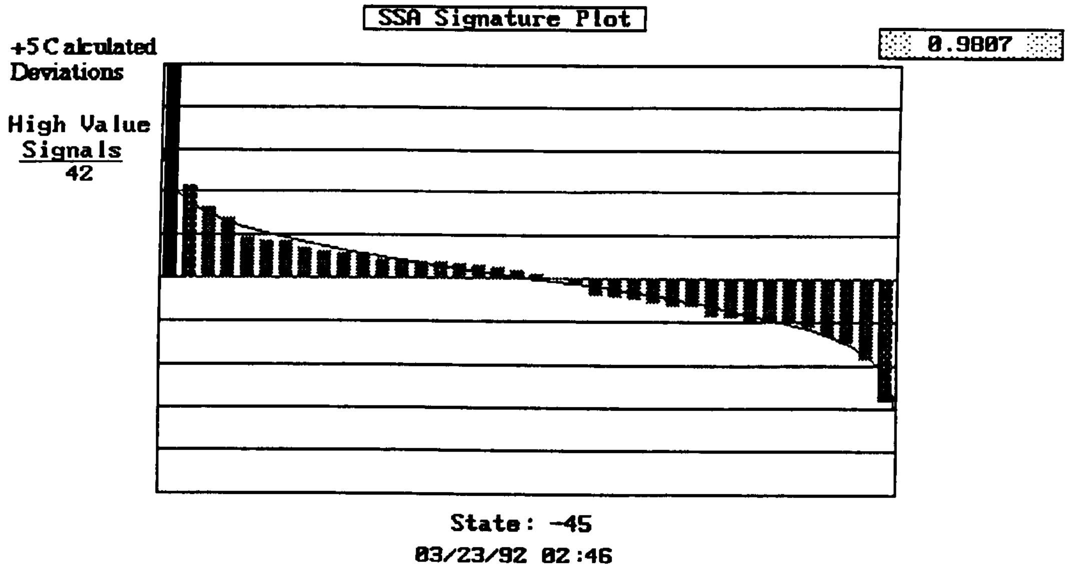

Figure 6. Signature Plot Showing Analysis Results Just After Pressurizer Spray Line Valve Test.

CONCLUSIONS

The pattern recognition software used by GPU detected a change in a steam generator level measurement before the magnitude of the change became an issue or caused a problem. The level change was detected at approximately 15% of the value that would have required a Technical Specifications calibration. The next regularly scheduled calibration brought the measurement back to normal and verified that the detected signal drift had been real.

The pattern recognition tool also detected a high temperature reading caused by a pressurizer spray line valve that did not completely reseat after routine testing. The small amount of leakage through the valve did not cause operational problems and was not significant enough to be detected by other means. The tool described in this paper is sensitive to small changes in monitored systems and can flag items for correction before other tools detect a problem.

The pattern recognition tool discussed in this paper has proven useful in the early detection of unusual changes in instrument readings at TMI Unit 1. A large number of measurements can be accurately monitored with little manpower expenditure, and with the possibility for correction before more serious problems occur. The tool can also be incorporated into on-line systems to provide a continuous validation of process data.

REFERENCES

(1) Empirical Models for Intelligent Data Validation, T. J. Harris, R. D. Griebenow, and R. Boring, EPRI/ISA POWID 35th Annual Power Symposium, June 1-3, 1992, Kansas City, MO.