State-of-the-Art Predictive Maintenance Techniques*

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***Abstract*—This paper discusses the limitations of time-based equipment maintenance methods and the advantages of predictive or online maintenance techniques in identifying the onset of equipment failure. The three major predictive maintenance techniques, defined in terms of their source of data, are described as follows: 1) the existing sensor-based technique; 2) the test-sensor-based technique (including wireless sensors); and 3) the test-signal-based technique (including the loop current step response method, the time-domain reflectrometry test, and the inductance–capacitance–resistance test). Examples of detecting blockages in pressure sensing lines using existing sensor-based techniques and of verifying calibration using existing-sensor direct current output are given. Three Department of Energy (DOE)-sponsored projects, whose aim is to develop online and wireless hardware and software systems for performing predictive maintenance on critical equipment in nuclear power plants, DOE research reactors, and general industrial applications, are described.**

***Index Terms*—Inductance–capacitance–resistance (LCR) testing, loop current step response (LCSR) method, predictive maintenance, time-domain reflectrometry (TDR) test, wireless sensor.**

I. Introduction

PREDICTIVE maintenance—sometimes called "online monitoring," "condition-based maintenance," or "risk-based maintenance"—has a long history. From visual inspection, which is the oldest method yet still one of the most powerful and widely used, predictive maintenance has evolved to automated methods that use advanced signal processing techniques based on pattern recognition, including neural networks, fuzzy logic, and data-driven empirical and physical modeling. As equipment begins to fail, it may display signs that can be detected if sharp eyes, ears, and noses are used to sense the failure precursors. Fortunately, sensors are now available to provide the sharp eyes, ears, and noses and identify the onset of equipment degradations and failures. Integrating these sensors with the predictive maintenance techniques described in this paper can avoid unnecessary equipment replacement, save costs, and improve process safety, availability, and efficiency.

Despite advances in predictive maintenance technologies, time-based and hands-on equipment maintenance is still the norm in many industrial processes. Nowadays, nearly 30% of industrial equipment does not benefit from predictive maintenance *technologies*. The annual calibration of equipment mandated by quality assurance procedures and/or regulatory regulations is a typical example of these time-based methods. In 2007, Emerson/Rosemount Company published data on the performance history of their pressure, level, and flow transmitters in various industries (excluding the nuclear power industry), where time-based and hands-on maintenance techniques are still the norm. The data showed that during periodic maintenance actions, technicians in these industries found transmitters to be experiencing no problems 70% of the time [1]. By contrast, in nuclear power plants, where online or predictive maintenance is used, this number is over 90% [2]. The data in [1] also showed that 20% of periodic maintenance actions revealed calibration shift problems (followed by sensing line blockage at 6% and failures at 4%). By comparison, only 5%–10% of periodic maintenance actions at nuclear power plants reveal calibration shift problems (though sensing line blockages occurred 10% of the time). The lower incidence of calibration faults in nuclear power plant pressure transmitters suggests that the online monitoring and predictive maintenance of equipment can reduce calibration problems in other industries as well.

II. Limitations of Time-Based Maintenance Techniques

Though time-based and hands-on equipment maintenance is still the norm in industrial processes, these techniques have increasingly been seen as flawed and unreliable in recent years [3]. Fig. 1 shows data on 30 identical bearing elements tested under identical conditions by SKF Group, a vibration and predictive maintenance analysis company. SKF engineers stressed the bearings to cause them to fail, then measured the time to failure. As Fig. 1 shows, some failed in fewer than 15 h, and others lasted ten times longer or more; one operated for 300 h. Despite the identical bearings and identical conditions, the time-to-failure varied by more than an order of magnitude. The conclusion to be drawn is that it is impossible to tell how long a component may last in an industrial process. It is therefore imprudent to set maintenance schedules based on failure time-based data like SKFs.

Fig. 2 shows six curves that are currently considered as failure models for industrial equipment such as pressure transmitters, all of which can be managed by periodic time-based maintenance activities. The three curves on the left-hand side—bath tub, wear-out, and fatigue—show the percentage of time that the failure characteristics of equipment may follow each of the three failure types. According to U.S. Department of Defense (DOD) data, however, these types of failures account for only about 11% of all failures [4]. The plots on the right-hand side of Fig. 2 show the following three more recent

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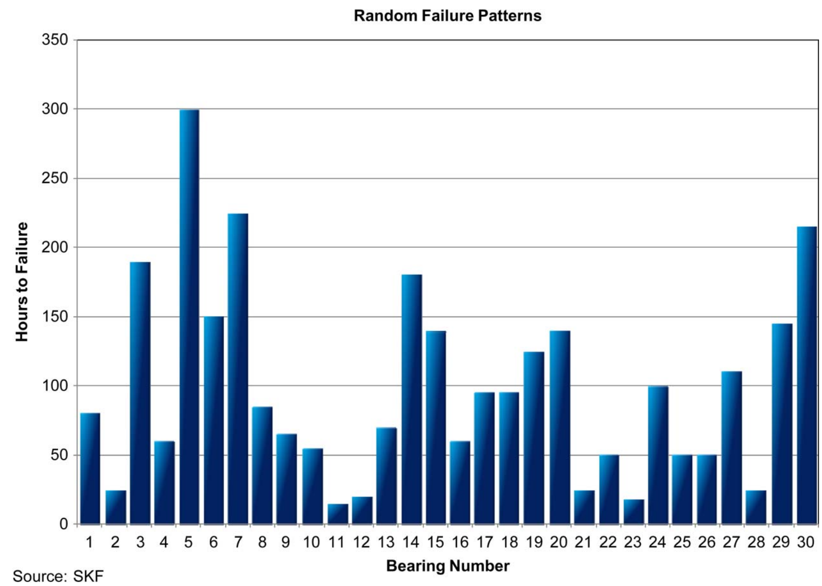


Fig. 1. Flawed time-based maintenance.

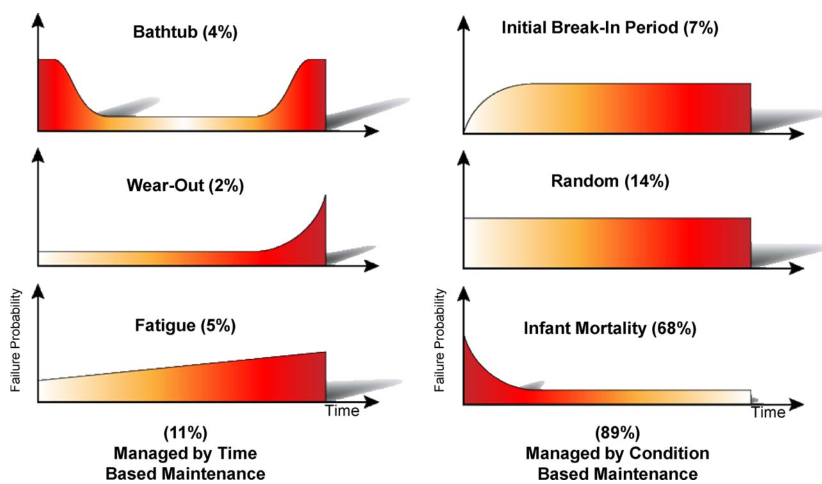


Fig. 2. Failure curves.

failure models that move past the time-based failure models: 1) initial break-in period model; 2) random failure model; and 3) infant mortality failure model. The DOD's data suggest that 89% of failures involve these three types, with infant mortality failures constituting by far the single largest type (68% of failures).

Although bath tub curve failures can be managed by periodic time-based maintenance activities, these activities are unreliable. The bath tub curve is an intuitive concept based on common sense and empirical knowledge rather than engineering or scientific principles. It was used for many years to formulate aging management programs in industrial processes and to establish equipment replacement schedules. The idea behind the bathtub curve is that the probability of failure of equipment is high when equipment is new ("infant mortality"). This is followed by a period of stable performance and lower failures (in which there are only random failures), which eventually leads to increased failure probability (known as the end-of-life or wear-out period). The bath tub curve is useful in that it suggests that to avoid infant mortality, equipment should be put through a "burn-in" process before they are installed in plants and that increased monitoring is desirable during equipment's end-of-life or wear-out period.

However, the bath tub curve cannot be used as the dominant model for equipment degradation and failure. According to Moubray, Nolan, and Heap, its accuracy in predicting the aging and eventual failure of equipment is only about 4%. Like other time-based failure models, the bath tub curve provides no precision regarding when end-of-life occurs [5]. The length of an equipment's stable period is never accurately known and will clearly vary for different types of equipment and the different conditions in which that equipment is used. For an industrial component such as a process sensor, a shaft in a motor, or tubes in a heat exchanger, maintenance and replacement schedules are not easy to establish. Following the bath tub curve, some plants replace equipment periodically (e.g., every 5–10 years) to avoid reaching the end-of-life. However, when a piece of equipment is replaced prematurely, the failure rate can actually *increase* because the new equipment may experience infant mortality.

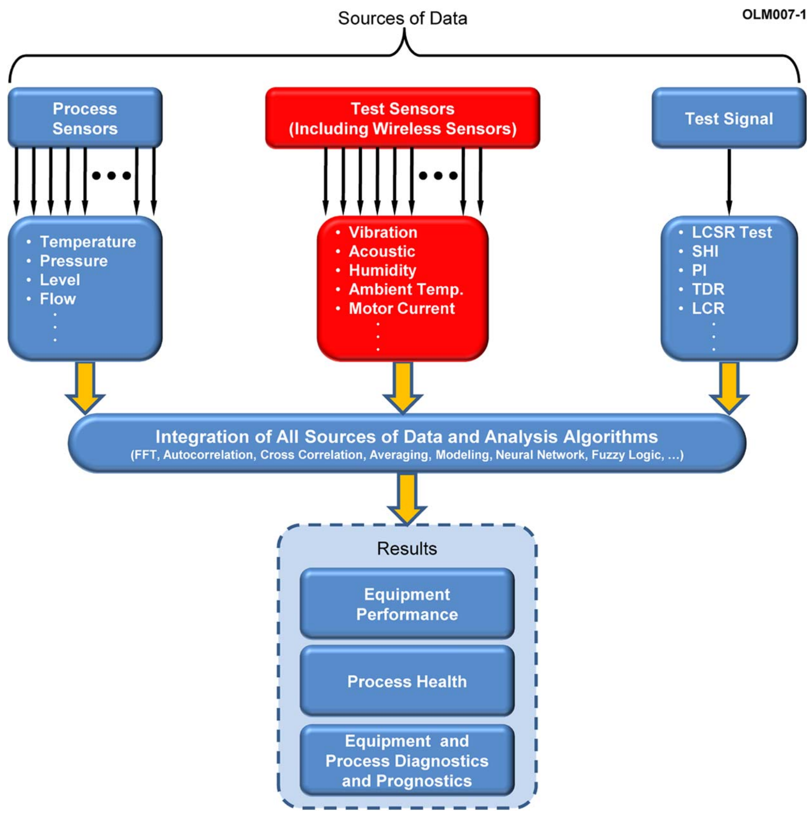


Fig. 3. Integrated system employing three categories of techniques for predictive maintenance of industrial sensors and equipment.

III. Predictive or Online Maintenance

As noted, predictive maintenance is the preferred maintenance method in 89% of cases, compared to time-based maintenance, which is prudent in only 11% of cases. Because of the unreliability of time-based maintenance methods, industrial processes should use online monitoring not only when equipment is old but throughout the life of equipment to identify the onset of degradation and failure of equipment.

One form of predictive maintenance, online calibration monitoring, provides an example of how predictive maintenance works. Online calibration monitoring involves observing for drift and identifying the transmitters that have drifted beyond acceptable limits. When the plant shuts down, technicians calibrate only those transmitters that have drifted. This approach reduces by 80%–90% the effort currently expended on calibrating pressure transmitters. This is according to data published by the author in a report he wrote for the U.S. Nuclear Regulatory Commission [6].

Predictive or online maintenance can be divided into the following three basic techniques (Fig. 3), based on their data sources: 1) the existing sensor-based maintenance technique; 2) the test-sensor-based maintenance technique; and 3) the test-signal-based maintenance technique. The first category consists of maintenance methods that use data from existing process sensors—such as pressure sensors, thermocouples, and resistance temperature detectors (RTDs)—that measure variables like temperature, pressure, level, and flow. In other words, the output of a pressure sensor in an operating plant can be used not only to indicate the pressure, but also to verify the calibration and response time of the sensor itself and to identify anomalies in the process such as blockages, voids, and leaks that can interfere with accurate measurement of process parameters or disturb the plant's operation, safety, or reliability. The second category of predictive maintenance methods uses data from test sensors such as accelerometers for measuring vibration and acoustic sensors for detecting leaks. This group of methods is where wireless sensors can play a major role.

These first two classes of predictive maintenance techniques are passive. In contrast, the third category of predictive maintenance technology depends on signals that are injected into the equipment to test them. This category includes active measurements such as insulation resistance tests and inductance, capacitance, and resistance measurements, also known as *LCR* testing. These methods are used to detect defects such as cracks, corrosion, and wear for the predictive maintenance of cables, motors, sensors, and other equipment. This third category of predictive maintenance techniques also includes the loop current step response (LCSR) method, which was developed in the mid-1970s by graduate students, professors, and technicians at the University of Tennessee (including the author). The LCSR method is routinely used in nuclear power plants for *in situ* response-time testing of RTDs and thermocouples as well as in other applications [7].

Table I lists the typical types of industrial equipment that can benefit from these three predictive maintenance technologies and the parameters that may be monitored. Table II lists examples of industries that can use the three types of online

TABLE I
PARAMETERS RELATED TO EQUIPMENT CONDITION

Equipment	Vibration	Humidity	Ambient Temperature	Ambient Pressure	Acoustic Signal	Thermography	Motor Current	Insulation Resistance	Electrical Capacitance	Electrical Inductance
Pump	✓		✓	✓	✓	✓	✓	✓		
Valve		✓		✓	✓					
Motor/Fan	✓		✓		✓	✓	✓	✓		✓
Heat Exchangers	✓	✓	✓	✓						
Steam Turbine	✓	✓	✓	✓	✓					
Electrical & Electronic Equipment			✓			✓		✓	✓	✓
Cables and Connectors			✓			✓		✓	✓	✓
Pump Seal		✓		✓	✓			✓		
Piping/ Structures	✓				✓					
Compressor	✓				✓	✓	✓			

TABLE II
APPLICATIONS OF EQUIPMENT CONDITION MONITORING

Industry	Process Optimization	Personnel Safety	Equipment Health	Emission Monitoring	Process Diagnostics	Equipment Performance	Leak Detection	Calibration Verification
Chemical	✓	✓	✓	✓	✓	✓	✓	✓
Petrochemical Refining	✓	✓	✓	✓	✓	✓	✓	✓
Pulp and Paper			✓		✓	✓		✓
Manufacturing	✓		✓		✓	✓		
Process Plants	✓	✓	✓	✓	✓	✓	✓	✓
Power Generation	✓	✓	✓	✓	✓	✓	✓	✓
Pharmaceutical			✓			✓		✓
Aluminum /Metals		✓	✓		✓	✓		
Health Care	✓	✓	✓			✓		✓
Defense Industry		✓	✓		✓	✓		

or predictive maintenance and the typical purposes for which each industry may use them. In 20–30 years, most industrial processes will have an integrated online condition monitoring system for performing automated predictive maintenance.

A. Category 1 Online or Predictive Maintenance Techniques: Existing Sensors

At frequencies usually below 30 Hz, existing process sensors can not only measure a process parameter, but can also provide plants with performance information. For example, pressure sensors can be used to monitor thermal hydraulic effects in addition to measuring pressure. Furthermore, standing waves, turbulence, and flow-induced vibration effects can be diagnosed using the normal output of existing pressure sensors in an operating process.

Fig. 4 shows how plants can use the output of existing sensors—the first group of online or predictive maintenance techniques—to verify the performance of the sensors themselves. The figure shows the normal output of a process sensor,

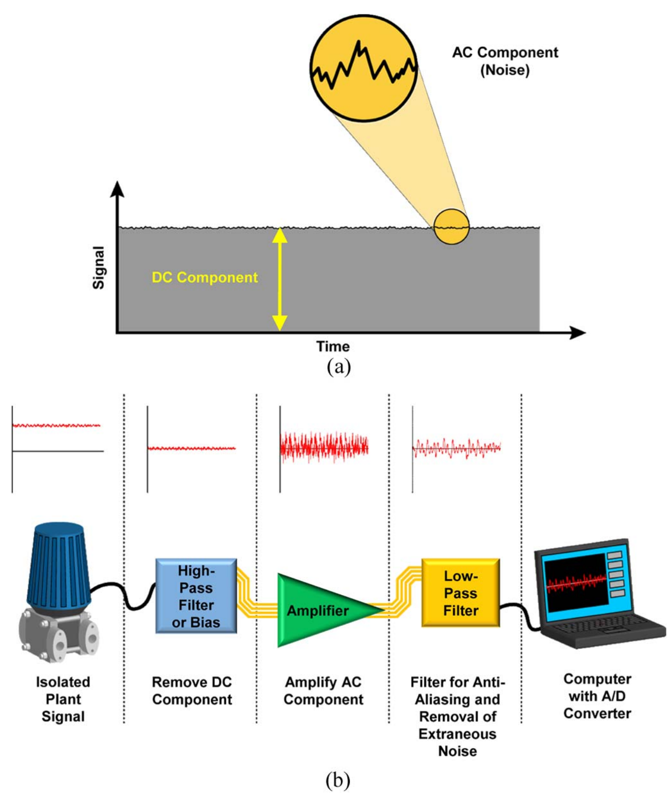


Fig. 4. (a) Typical output of a process sensor. (b) Separating the ac and dc components of a sensor output.

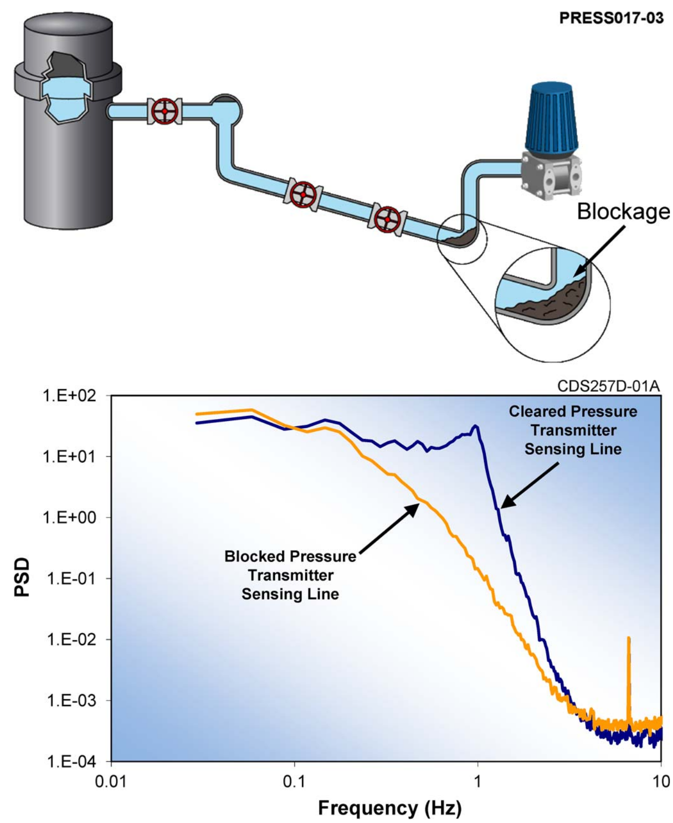


Fig. 5. Effect of sensing line blockage on dynamic performance of a pressure transmitter.

such as a pressure, level, or flow transmitter, plotted as a function of time. The dc component of the output is used to monitor for drift for online calibration monitoring, and the ac component of the output (referred to as noise) is used to verify the dynamic performance of the sensor (e.g., response time) and to identify sensing line blockages.

Fig. 4 also shows how the ac component of a sensor output is separated from its dc component and sampled into a computer through an antialiasing filter and then analyzed. The analysis usually involves performing a fast Fourier transform of the noise data. The results are presented in terms of a spectrum that is known as the power spectral density (PSD) of the ac signal. The PSD is actually the variance of the noise signal in a narrow frequency band plotted as a function of frequency.

After the noise data are analyzed, the PSD is used to calculate the response time of the pressure transmitter. An approximate value for response time can be estimated by noting the break frequency. To accurately measure response time, the PSD should be fit to a transfer function model of the sensor from which the response time is calculated.

1) Example—Using Existing Sensor AC Output to Detect Blockages in Pressure Sensing Lines: As noted, sensing line blockages are the second most common problem affecting pressure transmitters. Using existing sensor-based predictive maintenance techniques, one can identify the sensing lines that must be purged and cleared rather than having to purge all of them. This technique makes it possible to detect blockages while the plant is online using the normal output of pressure transmitters at the end of the sensing line [8].

Fig. 5 shows an application of this method. Two PSDs are shown in the lower right-hand plot—one for a partially blocked sensing line and the other for the same sensing line after it was purged of the blockage. These PSDs are taken from an analysis of actual noise data from a nuclear plant pressure transmitter. Observing the break frequency, it is clear that the blockage reduced the dynamic response of the sensor by an order of magnitude.

2) Example—Using Existing Sensor DC Output to Verify Sensor Calibration: Another example of existing sensor-based predictive maintenance techniques is verifying the calibration of process sensors using the dc output of the sensors. Fig. 6 shows the dc output of four redundant pressure transmitters from a nuclear power plant. The plot represents the deviation of each transmitter from the average of the four transmitters. It can be seen that the dc output of these transmitters did not drift over the two years shown. This fact could be used to argue that these four transmitters do not need to be calibrated. However, these data are based on only a one-point calibration check at the plant operating point. To verify calibration over the entire range of the transmitter, data should be taken not only at the operating point, but also at startup and shutdown periods. Fig. 7 shows calibration monitoring results for a pressure transmitter over a wide operating range. The limits shown in this figure represent the acceptance criteria for the allowable drift of this particular transmitter in this particular plant. These limits are calculated by accumulating the uncertainty values for the components that are involved in measuring this process parameter. The limits

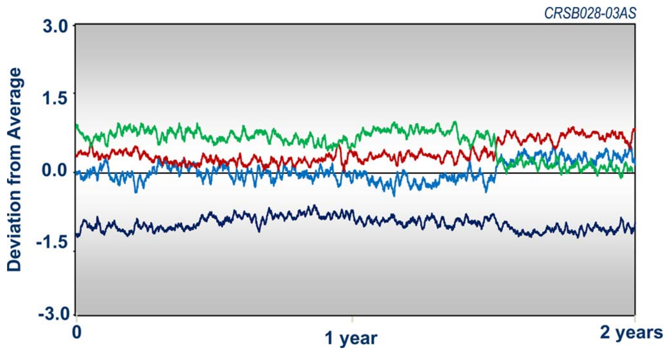


Fig. 6. DC output of four redundant pressure transmitters in a power plant.

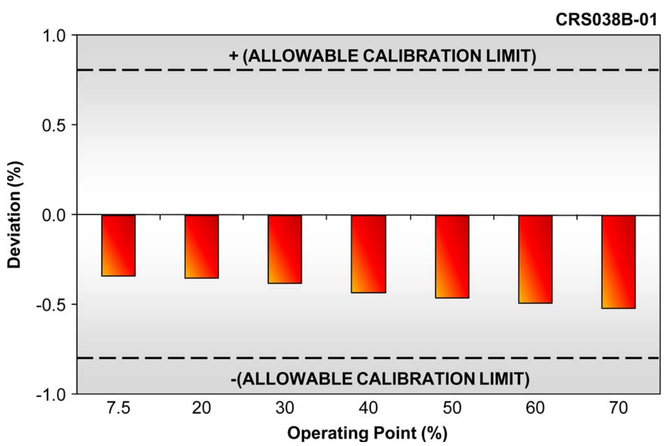


Fig. 7. Online monitoring results for calibration check of a pressure transmitter as a function of pressure range.

will differ for different transmitters in different plants, depending on the methodology used to calibrate the instruments.

To facilitate the use of existing sensor-based predictive maintenance, the author and his colleagues have developed software for measuring sensor calibration online. Fig. 8 shows the software screen, which consists of four windows of data. The window on the top left presents the raw data for nine transmitters during a plant shutdown. Below this is a plot of the deviation of each of the transmitters from the average of the nine. The calibration limits are also shown in this deviation plot. The bottom-right window is a plot of calibration error for each transmitter as a function of its operating range. The table in the upper right shows the results of the calibration monitoring: eight transmitters passed the calibration monitoring test; one failed it.

3) Using Empirical or Physical Modeling to Verify Calibration: In some cases, a process will not have enough redundant existing sensors to provide a reference for online calibration monitoring. In these cases, in addition to averaging the redundant sensors, the process can be modeled empirically to create analytical sensors [9]. This method is illustrated in Fig. 9. Note that both physical and empirical models can be used to create analytical sensors.

Using empirical modeling, plants can identify not only calibration problems, but also other instrument anomalies such as fouling of venturi flow elements in power plants. This is illustrated in Fig. 10, which shows reactor power as a function of time. Two traces are shown. One is from empirical modeling of the reactor for the purpose of calculating actual power, and another is from the plant power-level indication system. The indicated power trends upward, erroneously, while the actual power is stable, as it should be. The reason for the discrepancy is fouling of the venturi flow element. As venturi fouls, the indicated flow rate rises and causes the power indication to rise accordingly. Analytical modeling, such as by empirically modeling the plant process using neural networks, enables plants to identify the onset of venturi fouling and to see the extent of error in the indicated power. Fig. 10 shows that in this example, at 500 days of operation, the error is about 2.5% in power.

B. Category 2 Online or Predictive Maintenance Techniques: Test Sensors, Including Wireless

The second category of online or predictive maintenance techniques is, like the first, passive. However, rather than relying on existing sensors for its data, they use data from test or diagnostic sensors. Typical examples of test sensors are accelerometers for measuring vibration and acoustic sensors for detecting leaks. For example, acoustic sensors installed downstream of valves can establish whether the valve is operating as expected: if a valve is completely open or completely closed, there is normally no detectable acoustic signal above the background noise.

When existing test sensors are not available to provide the necessary data, wireless sensors can be deployed to fill the gap. For example, wireless sensors can be implemented in such a way as to combine vibration, acoustic, and other data with environmental information such as humidity and ambient temperature to yield a comprehensive assessment of the condition of the process's equipment and health.

Wireless sensors can facilitate difficult measurements in industrial processes where wiring is a weak link, such as flame temperature and high furnace-temperature measurements. Wireless sensors also facilitate measurement in hazardous environments and in applications where space for wiring installation is limited. Wireless sensors can also be the answer to the threat posed by rust, corrosion, steam, dirt, dust, and water to wires in industrial facilities. With wireless sensors, data can be collected from anywhere and routed on to the Internet where they can easily be accessed and analyzed. Finally, wiring costs in an industrial process can be as high as $2000 per foot versus $20 per foot if wireless equipment were used for the same applications. Wireless sensors promise to enhance industrial productivity, lower energy and material costs, and increase equipment availability.

According to a 2007 survey of engineering professionals in the International Society of Automation's InTech magazine, wireless technologies are the largest area of technology growth in the near future [1].

To promote the growth of wireless-based predictive maintenance, the Analysis and Measurement Services (AMS) Corporation has developed a software package, called "Bridge," that is able to read data from wireless sensors from different

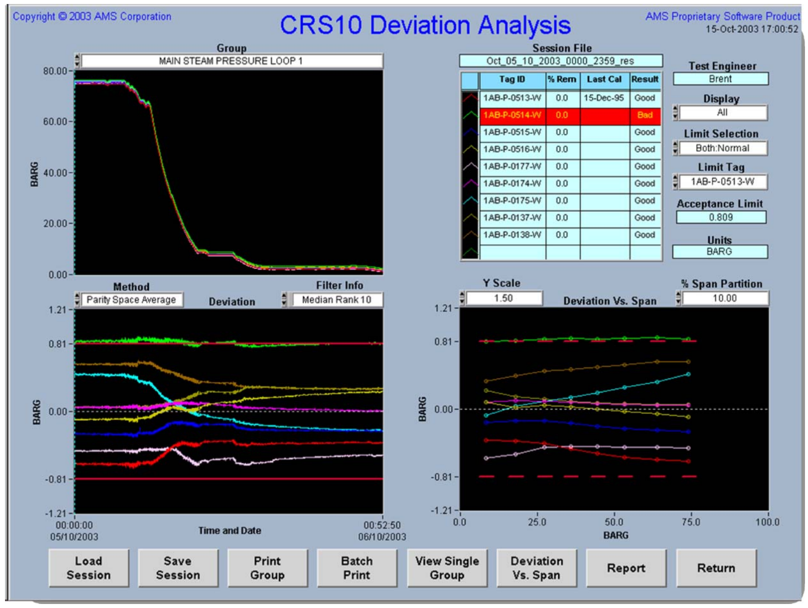


Fig. 8. Software screen with results of online calibration monitoring.

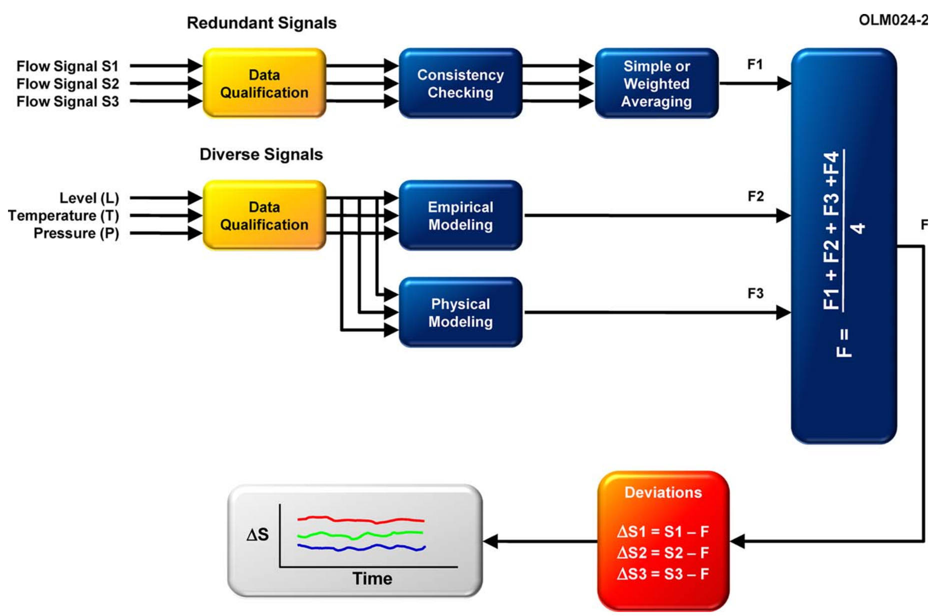


Fig. 9. Conceptual design of analytical sensor for online calibration monitoring.

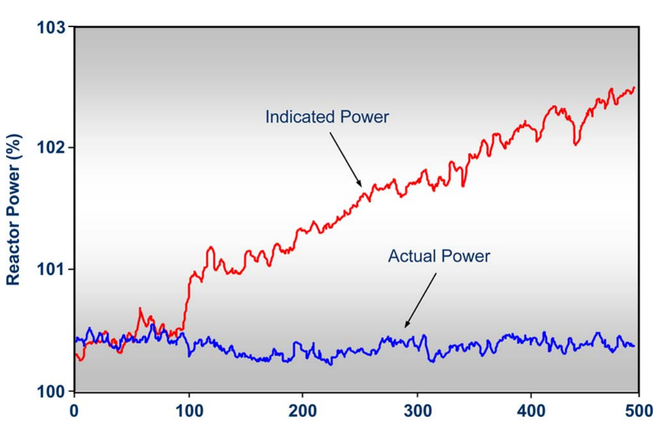


Fig. 10. Detection of venturi fouling.

manufacturers, bringing all of a plant's wireless data together in one place in one format so it can be analyzed and compared.

C. Category 3 Predictive or Online Maintenance Techniques: Test Signals

The first two categories of predictive maintenance techniques were mostly passive, do not involve perturbations of the equipment being tested, and can be performed in most cases while the plant is operating. The third category of predictive maintenance methods can be described as methods that depend on active measurements from test signals.

One form of test-signal-based predictive maintenance involves injecting a signal into the equipment to measure their performance. For example, a method called the LCSR test can remotely measure the response time of temperature sensors as

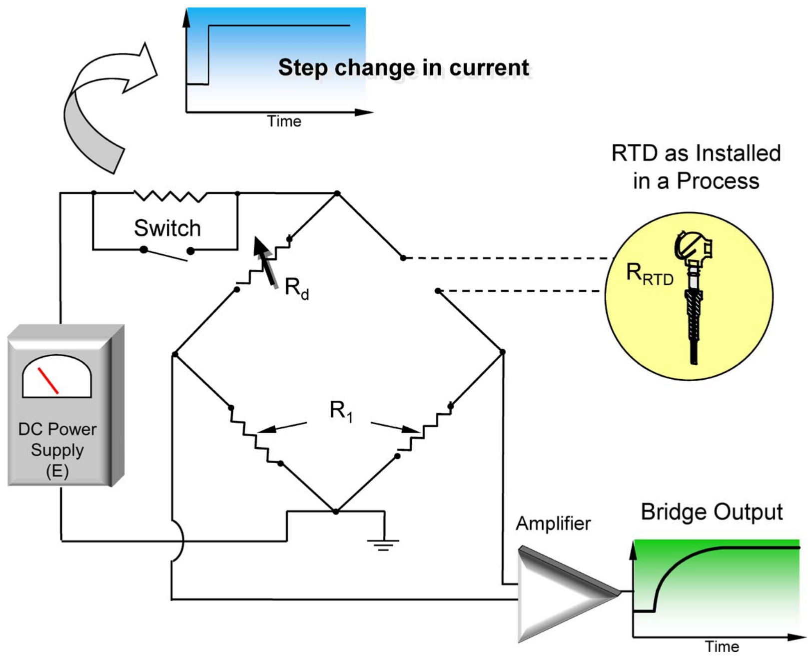


Fig. 11. Principle of LCSR test for *in situ* measurement of an RTD response time.

installed in a plant while the plant is online [7]. This method sends an electrical signal to the sensor in the form of a step change. Fig. 11 shows the setup for performing LCSR on an RTD. A Wheatstone bridge is used to send a step charge in current to the RTD. The current causes heating in the RTD sensing element and produces an exponential transient at the bridge output. This transient can be analyzed to give the response time of the RTD. The LCSR test can be used for other purposes such as finding water levels in a pipe. It can also be used to verify that temperature sensors are properly installed in their thermowells in a process and that they respond to temperature changes in a timely manner. Similarly, the LCSR method can be used to determine if aging causes degradation in the dynamic performance of temperature sensors so sensor replacement schedules can thereby be established. In 1979, the author helped use the LCSR technique during the Three Mile Island nuclear plant accident to assist the plant to determine water level in the primary coolant pipes. Finally, the LCSR method can also be used to detect the bonding of sensors such as RTDs and strain gauges to solid surfaces (Fig. 12).

Fig. 13 shows the response time of several thermocouples measured by the LCSR test. There is one outlier, which had a secondary junction that was not at the tip of the thermocouple, causing its response time to be much higher than the others. The LCSR method helped identify that this thermocouple's measuring junction is not where it should be and thus indicated an erroneous temperature.

Test-signal-based predictive maintenance methods also include the time-domain reflectometry (TDR) test. It is used to locate problems along a cable, in a connector, or at an end device by injecting a test signal through the conductors in the cable and measuring its reflection. The TDR technique has also served the power and process industries in testing instrumentation circuits, motors, heater coils, and a variety of other components. In a TDR test, a step signal is sent through the cable, and its reflection is plotted versus time. The plot will show any changes in impedance along the cable, including at the end of the cable.

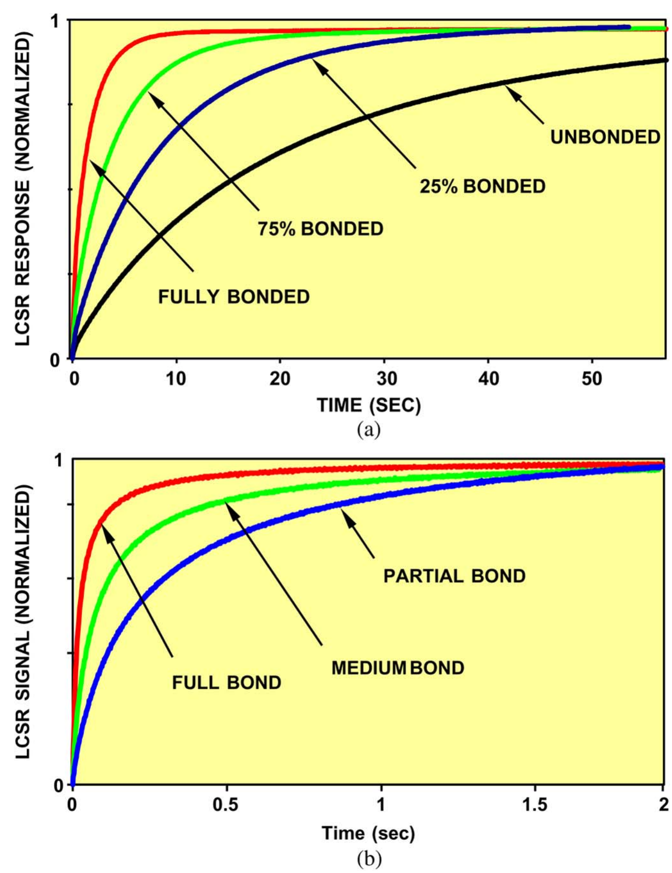


Fig. 12. (a) LCSR can determine the degree of bonding of temperature sensors to solid surfaces. (b) LCSR can determine the degree of bonding of strain gauges to solid surfaces.

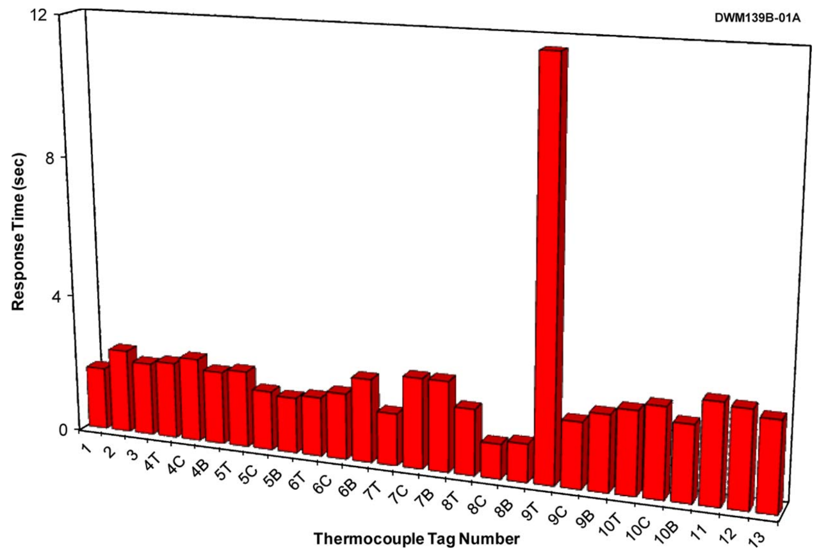
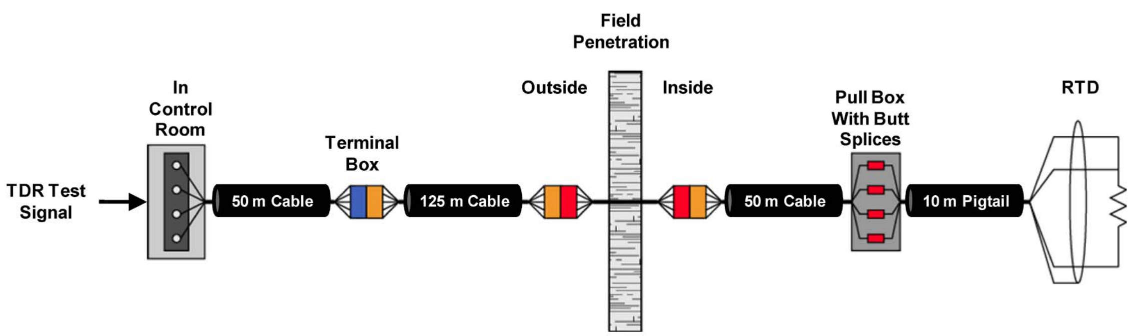
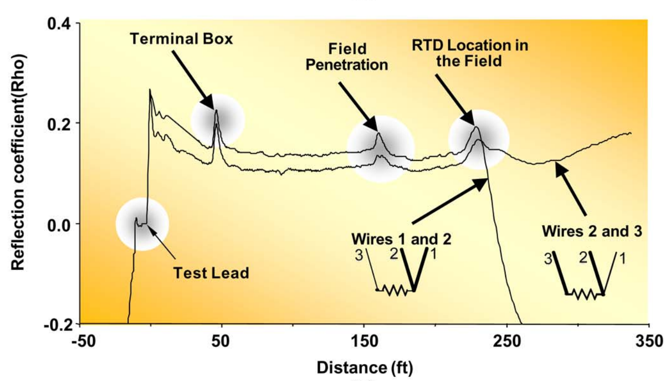


Fig. 13. LCSR for *in situ* testing of a thermocouple problem.



(a)



(b)

Fig. 14. (a) RTD circuit. (b) TDR test results of the RTD circuit.

Fig. 14 shows the TDR of a three-wire RTD as installed in a plant. It clearly shows all locations where there is a change in impedance, including the end of the cable that has an RTD. If the TDR is trended, problems that may develop along the cable or at the end device can be identified and located. The simplest application of TDR is locating an open circuit along a cable. You can tell if the circuit is open by measuring its loop resistance, but only a TDR would tell you where the circuit is open. Fig. 15 shows how TDR identified a failed RTD in a nuclear power plant, where knowing if the open circuit is inside the reactor containment or outside the reactor containment is critical. Fig. 16 shows a TDR of a thermocouple measured in 1999 and 2008. The 2008 data indicate that the thermocouple impedance has changed significantly.

A complementary set of cable tests that measure impedance, called *LCR* testing, is often used in addition to TDR to identify whether a circuit problem is caused by an open circuit, a short circuit, a shunt, a moisture intrusion, or other problems. Alternatively, one can perform an *LCR* test by itself to measure cable inductance and capacitance and trend the values to identify problems or compare against a baseline. Typical cable circuits can be characterized both by series inductance and

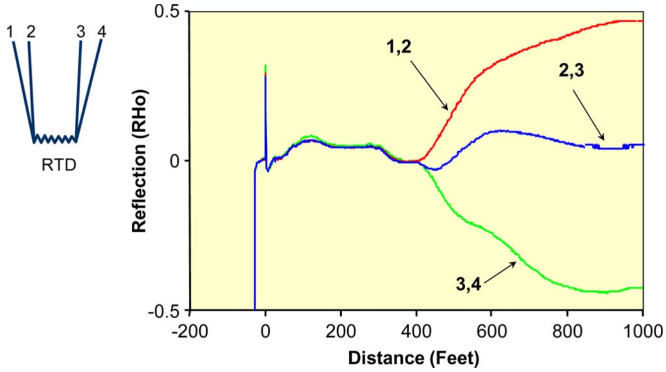


Fig. 15. Failed RTD detected by TDR.

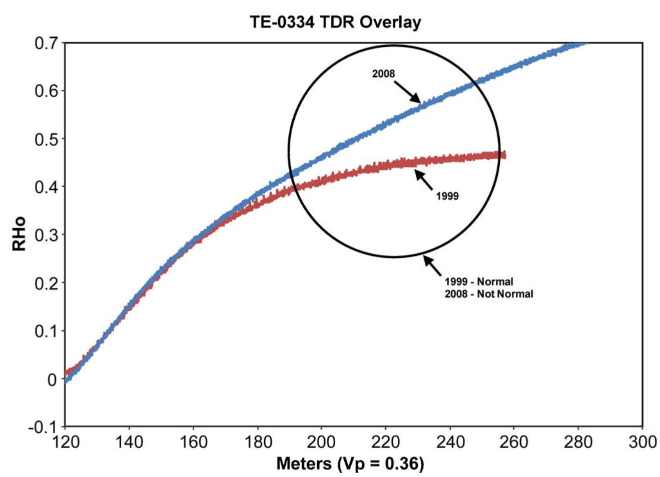
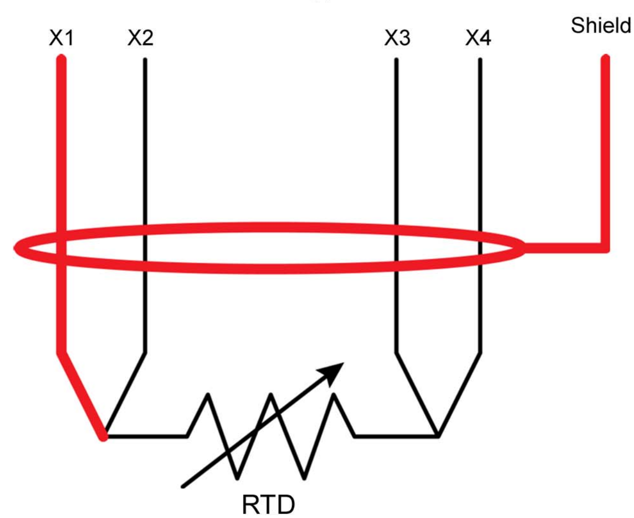


Fig. 16. Results of TDR monitoring of a thermocouple.

ITEM	RTD I.D.	CAPACITANCE (NANOFARAD) (@ 1 KHZ)	DISSIPATION FACTOR
1	451	225.6	0.088
2	461	237.6	0.094
3	471	244.7	0.099
4	481	230.0	0.094
5	622	238.0	0.099
6	623	225.7	0.097
7	624	233.8	0.090
8	625	236.7	0.094
9	626	226.8	0.090
10	627	228.4	0.094

(a)



(b)

Fig. 17. (a) Capacitance measurement results for ten RTDs and dissipation factor calculations (for lead X1 to ground). (b) RTD circuit for the results shown in this table.

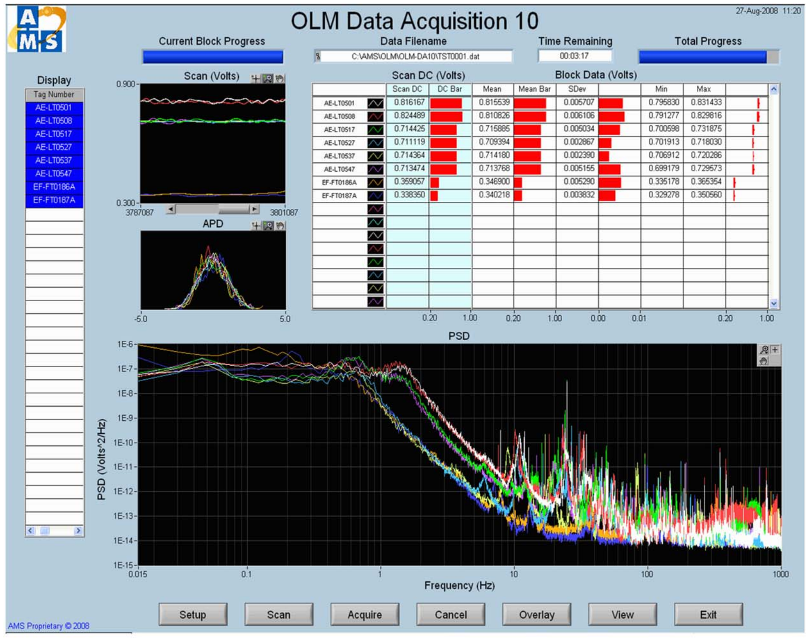
resistance and by parallel capacitance of the dielectric. Fig. 17 shows capacitance measurement results for ten RTDs as well as dissipation factor calculations. These are all normal values.

Although using TDR and *LCR* measurements is not complicated and they have been used for many years, their applications in industrial processes are still new.

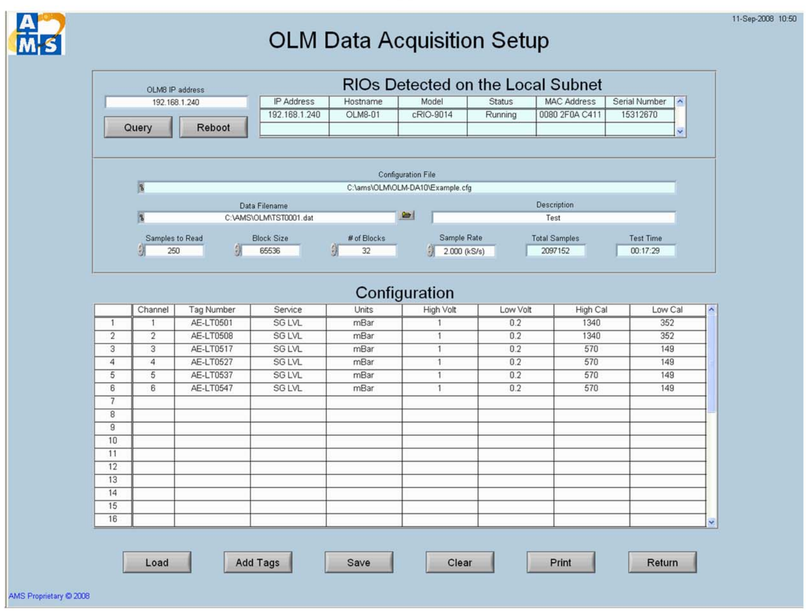
IV. Predictive Maintenance R&D Projects

The three predictive maintenance technologies discussed in this paper are part of three U.S. DOE projects under the Small Business Innovation Research program to subsidize R&D work at small (under 500 employees) high-technology firms that can convert the R&D results into commercial products. The goal of the first of these projects, namely, "On-Line Monitoring of Accuracy and Reliability of Instrumentation," is to develop systems for online condition monitoring of equipment and processes in industrial plants. As noted previously, the goals of the second project, namely, "Wireless Sensors for Equipment Health and Condition Monitoring in Nuclear Power Plants," are to develop data qualification and data processing techniques for wireless sensors, to identify which parameters these sensors should measure, and to determine the correlation between these parameters and the actual condition of the equipment being monitored. The goal of the third project, namely, "Wireless Sensors for Predictive Maintenance of Rotating Equipment in DOE's Research Reactors," is to determine the feasibility of using wireless sensors to monitor the condition of equipment in research reactors such as the high-flux isotope reactor (HFIR) at the Oak Ridge National Laboratory.

Since the wireless and HFIR projects are still under way, we will focus here on the progress made in the Online monitoring (OLM) project. The OLM project is aimed at developing new technology that uses signals from existing process sensors to verify the performance of the sensors and assess the health of the process. The work involves both software and hardware development, testing, and validation using existing hardware and software that have been adapted to the project. The software packages we developed are for data acquisition, data qualification, and data analysis equipment. This equipment is designed for fast data acquisition and will be used for ac and dc data acquisition. The AMS Corporation is currently adapting



(a)



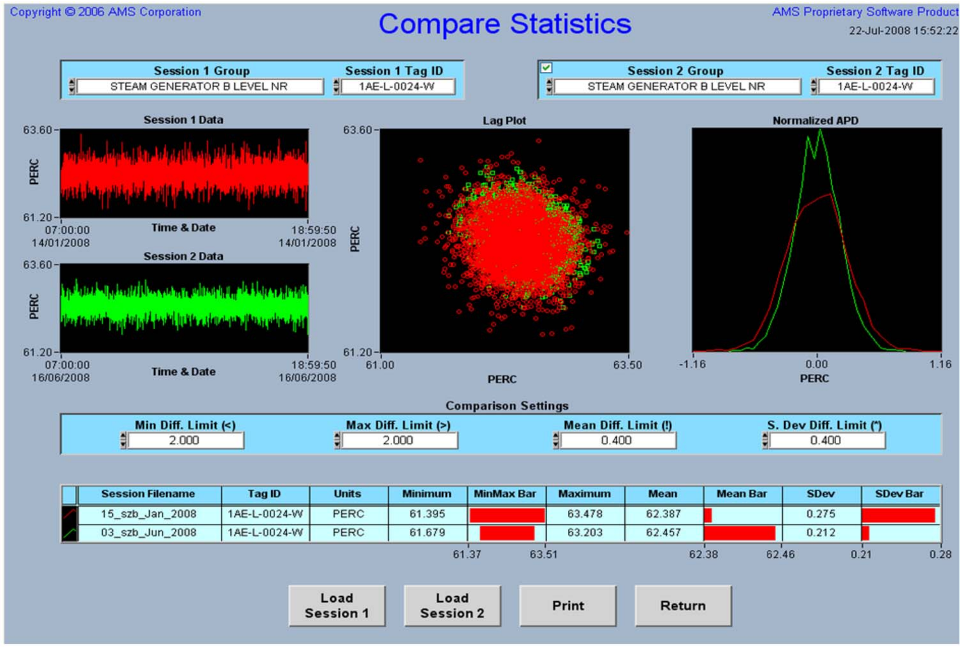
(b)

Fig. 18. (a) and (b) Screenshots of OLM software.

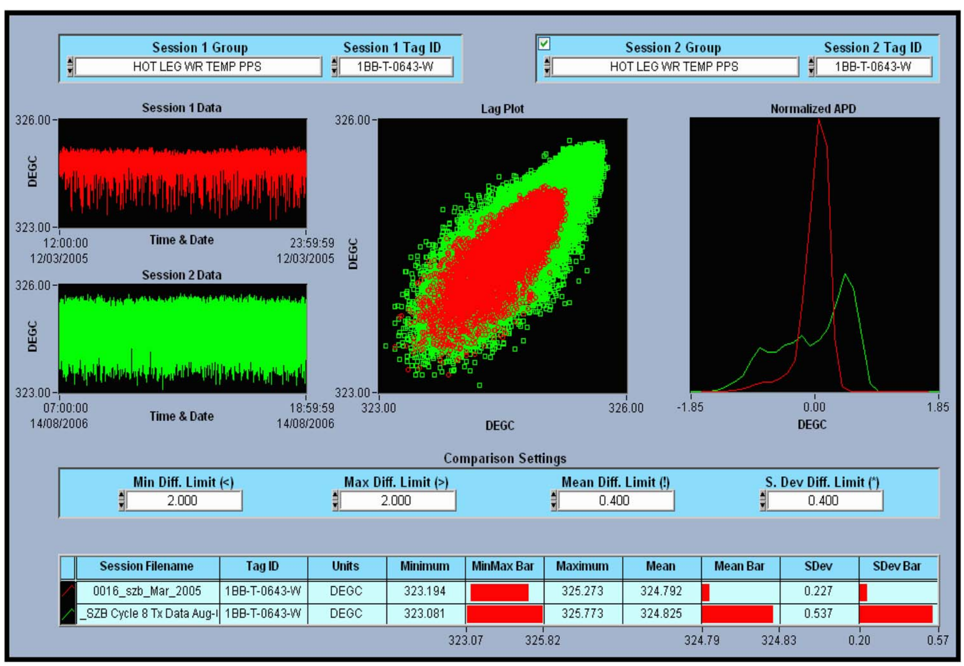
National Instruments Company's new data acquisition product CompactRio to the OLM project. Writing the algorithm and software packages and testing and implementing a prototype system in an operating plant constitute the bulk of the OLM project's current work. Fig. 18 shows software screenshots of an ac signal analysis to detect dynamic anomalies in equipment and processes, and Fig. 19 shows software screens of data qualification results before they are analyzed. Under the OLM project, the AMS Corporation is developing statistical packages for data qualification. For example, we calculate the amplitude probability density of the data and look for nonlinearity and other problems in the data before we send the data through for analysis. We also calculate signal skewness, kurtosis, and other measurements and trend them to identify problems in data.

V. Conclusion

Industrial plants should no longer assume that equipment failures will only occur after some fixed amount of time in service; they should deploy predictive and online maintenance strategies that assume that any failure can occur at any time (randomly). The onset of equipment failure may manifest itself in data generated by the methods used to monitor the equipment, providing clues as to whether the equipment should be repaired, replaced, or left to continue in operation. Ongoing research into the three major types of predictive or online maintenance technologies discussed in this paper promises to deliver technologies that may be applied remotely, passively, and online in industrial processes to improve equipment reliability, predict failures before they occur, and contribute to



(a)



(b)

Fig. 19. (a) and (b) Data qualification results.

process safety and efficiency. Integrating the predictive maintenance techniques described in this paper with the latest sensor technologies will enable plants to avoid unnecessary equipment replacement, save costs, and improve process safety, availability, and efficiency.

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