Predictive Analytics in Equipment Reliability Programs

Predictive Analytics in conjunction with Threat Based Maintenance™ (TBM™) reduces and, in some cases, can eliminate the need to perform time-based maintenance. Data mining by operations, technicians, and engineering personnel also can be reduced or eliminated because Predictive Analytics detects many problems automatically. By drawing attention to abnormal equipment behavior, Predictive Analytics optimizes equipment monitoring, resulting in increased maintenance lead time and reduced maintenance and operating costs.

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Predictive Analytics uses data historians, modern networking, and Similarity Based Modeling (SBM) software technology. SBM identifies small deviations in equipment behavior that are precursors to potential failure. Predictive Analytics focuses resources on the equipment that needs attention, reducing wrench time for plant personnel.

Innovation life cycle

The Technology S-Curve describes the innovation life cycle for technology and processes. New inventions or ideas follow a consistent life-cycle pattern: new technology, technology improvement, technology maturation, and aging technology (Figure 1).

Predictive Maintenance (PdM), Condition Based Maintenance (CBM), and Reliability Centered Maintenance (RCM) are all mature technologies, with proven return on investment. In the nuclear industry, PdM was implemented to support in-service testing. As the benefits of PdM were realized, CBM was introduced to optimize time-based preventive maintenance and to verify the conditions of both BOP and safety-support-system equipment. The nuclear industry has recognized the maturity of these methodologies through AP-913.

The AP-913 structures that nuclear utilities are implementing to improve the current plant reliability processes and to increase the overall effectiveness of plant reliability through optimization of CBM and time- based PdM are effective but mature. Additional innovation is needed to continue to improve availability and reliability in nuclear power plants.

RCM, CBM, and PdM together optimize preventive maintenance and increase capacity factor. However, plants that have implemented these approaches have seen their gains in reliability, availability, and capacity factor flatten and stagnate. The RCM technology cycle is beginning to mature and age and, as a result, new innovation in the area of reliability is needed to continue the push for improvement. This paper describes how Predictive Analytics, supporting the new Threat Based Maintenance methodology, can continue to provide gains in reliability and availability by early detection of emerging threats to critical equipment (Fiure.2).

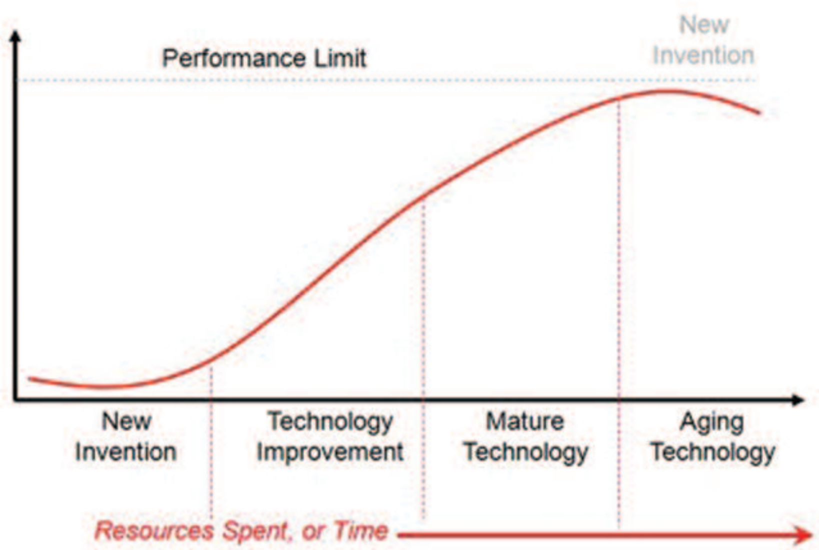

Figure 1: Moore's Law and the Technology S-Curve, by Murrae J. Bowden

Higher plant performance

In today's centralized monitoring of plant processes and systems, the amount of data being retrieved, recorded, trended, viewed, and alarmed is growing exponentially. As the amount of data increases, the ability to make sense of the data overload often rests on system engineers.

The need to detect abnormal behavior before it affects the operation in a nuclear power plant is fundamental to improving availability and reliability. Typically, the alarming system set by OEMs is directly related to protection of people and equipment from ancillary damage caused by the abnormal condition. For example, the high temperature alarm on a pump or motor bearing is designed to reduce the damage to the asset; however, typically, by the time the alarm occurs, the damage to the component already has occurred.

In-service testing of safety-related components historically has been used as a springboard to bring CBM into nuclear power plants. The rationale for CBM is to monitor all the plant critical equipment, including safety-related or critical to power production, in order to detect the onset of a failure so engineering and operations can make a determination of the potential impact to safety, reliability, and availability. The data collected is used to assist maintenance in planning and scheduling of work proactively versus reactively.

TBM expands the concept of monitoring and incorporates Predictive Analytics to detect changes in equipment behavior that are precursors to potential failure. Embedded within the TBM philosophy is the idea that these precursors and emerging problems are "threats" that, if allowed to progress, can potentially impact availability and increase maintenance costs. With advanced notice and focus on threats to equipment, the system engineer, maintenance, and operations personnel have the advanced notice they need to move nuclear power maintenance into the proactive mode that has been the promise of RCM, CBM, and PdM systems.

TBM uses Predictive Analytics to increase the time between "change in behavior" and "need to take action." This gives the plant more time to evaluate and plan corrective actions. In many instances, advanced notification allows repair actions that mitigate the failure of components and alleviates the need to perform invasive maintenance.

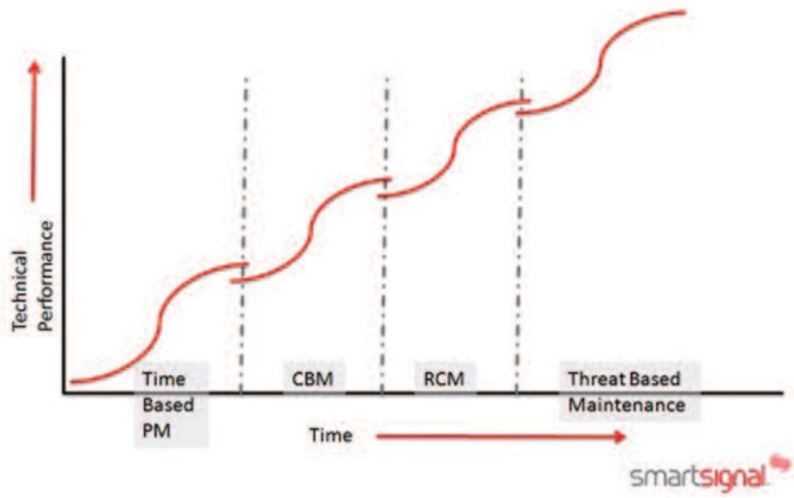

Figure 2: Adding value to mature innovation

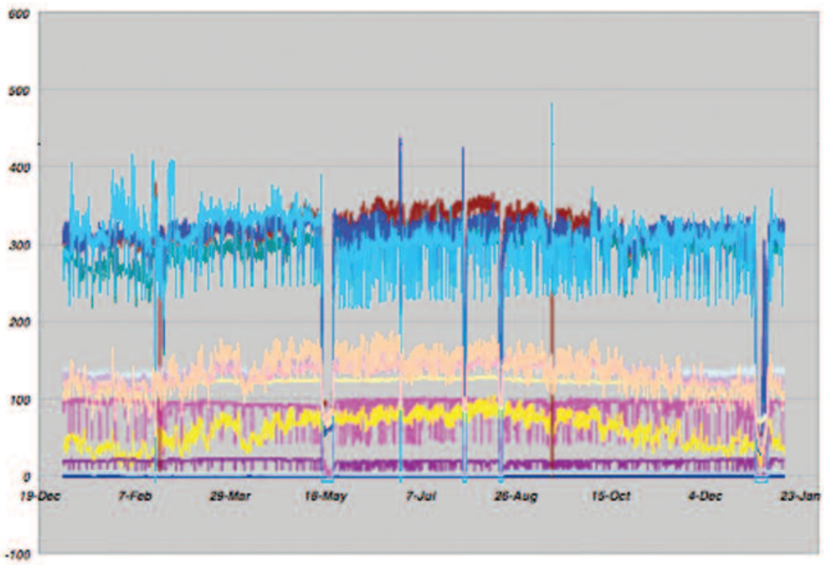

Figure 3: Sensor Data Chaos

Predictive Analytics

Predictive Analytics in systems trend analysis is the use of specialized software packages to analyze, in near real time, data collected from processes and equipment. The software applies a Predictive Analytics model to the sensor data and returns information on the behavior of the individual sensors in the model.

If a parameter deviates from the historical normal process, taking into account ambient and process conditions, the software alerts the systems engineer of the deviation so analysis and action can be focused on the abnormal behavior. Deviations can be as simple as a sensor failing or as complex as efficiency losses in a turbine generator. Early detection and differentiation in the levels of risk and urgency significantly improve a system engineer's focus and ability to trend, forecast, and schedule asset maintenance.

These tools have the potential to transform a system engineer's daily activities. The increase in plant system data further underscores the importance of an automated means to determine what is normal. Advanced Predictive Analytic software tools have become essential for mining data trends that indicate change in behavior of the asset. Armed with this data, the engineer can focus resources on determining the cause and formulating the best response. Predictive Analytics doesn't eliminate the human element of analysis or action. The technology aids in scanning vast quantities of data quickly and making

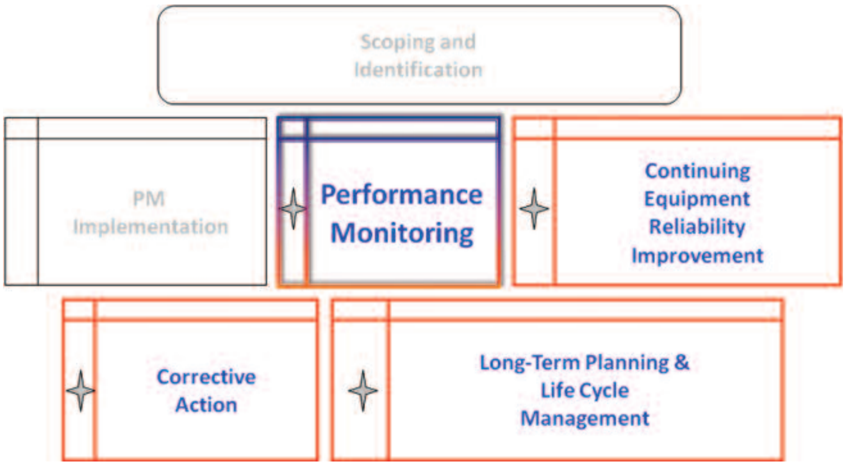

Figure 4: AP-913

sense of it. Raw sensor data, for example, can appear to be chaos: In Figure 3, there are only 14 sensors, yet it challenges the human mind to view, much less organize, the resulting data. Is this data normal? Can you detect deviations from normal? Is there an imminent functional failure lurking in the data? Traditional alert limits can assist in protecting equipment and personnel, but they don't substantially protect or improve availability and reliability.

Using a Predictive Analytic system, engineers do not need to be involved in direct data trending activities. Data is monitored by the software, and the engineers review the data when an exception is posted, with ample time to respond to an aberrant or changing condition. By highlighting only signals deviating from normal expected patterns, monitoring efforts always are efficient. The engineer no longer has to search all signals for visible problems.

Efficiency can be equated with increasing the engineer's scope of monitoring capability and insight or, concurrently, reducing the person-power required to do the job. By performing Predictive Analytics routinely and continuously (every 5-10 minutes for the typical nuclear power application), the resulting analysis is near real-time. By using algorithms to identify pattern changes earlier than the human eye even can detect, the analysis is highly accurate. By using specific historical data from the equipment or system to "train" the models (reducing the need for prior data or operator knowledge), the result is "smart" analysis.

Accuracy component of Predictive Analytics—similarity based modeling

The modeling technique used in Predictive Analytics is called Similarity Based Modeling (SBM). In brief, SBM models a group of related signals by analyzing historical data to identify the normal pattern of behavior of the signals. The patterns identified then are put on-line and used to analyze each sample of data collected. From the pattern, an estimate of each signal's behavior is generated and compared to the actual real-time value. The difference between the expected and actual, also referred to as the residual, is continuously compared to empirical thresholds.

If the comparison is abnormal, preset rules fire, which draw the attention of the analyst. SBM modeling accuracy typically exceeds requirements for most applications. Since SBM considers a group of signals and compares the behavior of a signal relative to the behavior of all the other related signals, it offers a more accurate checkpoint for deviations from historical patterns of behavior.

One significant advantage of using SBM is that signals can be modeled together when they are physically linked in behavior. Using a pump model as an example, the current, speed, inlet valve position, motor bearing temperatures, motor bearing vibrations, pump bearing temperatures, pump bearing vibrations, and pump flow all can be modeled together. No regression or other parametric analysis need be done. The parameters all move relatively together in identifiable patterns of behavior which are recognizable using SBM, which is superior to an engineer using monitoring disciplines and techniques that often are conducted separately.

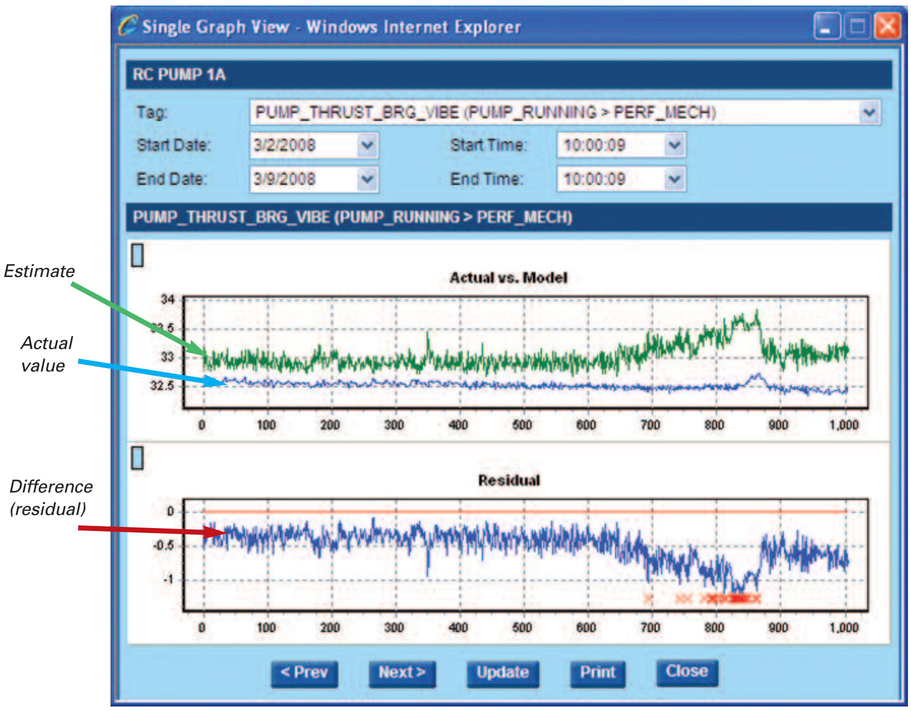

Figure 5: Sensor View

Threat based maintenance and Predictive Analytics in AP-913

AP-913 was introduced by INPO to assist utilities in coordinating an asset reliability

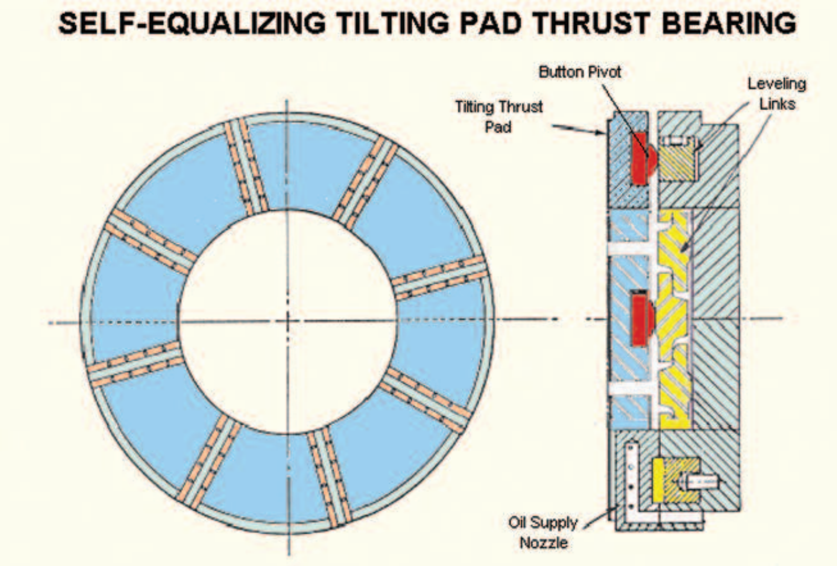

Figure 6: Thrust Bearing

system to improve safety, reliability, and availability in the nuclear industry. In Figure 4, part of AP-913 addresses the monitoring of plant systems both for safety-related and Balance of Plant systems and components. This monitoring places a burden on system engineers or system managers to monitor and trend their systems for deviations from normal operation. Predictive Analytics assists the system engineers in monitoring their systems for abnormal behavior and improving overall system health.

AP-913 Section 2 states "Compare the actual performance to criteria. At regular intervals, system experts will trend the plant data used to determine system/train performance against the established performance criteria." (AP-913, Revision 1)

When a system is considered to be running in optimal condition, the easiest way to monitor performance is to compare real-time data to the historical operating condition, noting deviations from the normal condition. With the large number of sensors now monitoring a nuclear plant's assets and processes, detecting early drift off of normal is handled by system engineers utilizing methods that typically are individualized by utility and, sometimes, by the individual engineer.

One method to trend data uses the data historian, with an engineer "looking" for changes. Other methods include exporting the data to a spreadsheet and writing custom calculations to determine the change from normal and comparing the sensor data to first principle curves developed for the component (e.g. pump curves). All are applicable methodologies, but all have one common weakness: engineering time to download, export, manipulate, and examine the data.

Predictive Analytics and the TBM philosophy fit well within the AP-913 framework and automate much of the work. With automated data analysis, it also becomes possible to expand the range of data and equipment beyond what might be practical with manual methods.

Improved trending with Predictive Analytics

Predictive Analytics is not new in the nuclear industry. It originally was developed specifically for nuclear power plant equipment online monitoring. Predictive Analytics uses modeling techniques and algorithms to incorporate sensor information around an asset and to determine changes in behavior from the historical operation of that asset. This predictive technology is very accurate in modeling the behavior of an asset. If a sensor deviates from historical operating conditions, the system will notify the end user of the deviation. This assists the engineer in monitoring the plethora of sensor data and focuses attention on abnormal behavior.

Predictive Analytic software allows the system engineer to "drill" down into the data from the asset and compare the sensor to the modeled behavior of the sensor (Figure 5). This focuses the engineer on abnormal deviations of an asset versus the proverbial "needle-in-the-haystack" trending. Although nuclear system engineers are highly effective in trending and monitoring their systems, the ability to focus on abnormal behavior earlier in a problem lifecycle reduces the burden on the engineer to identify potential threats.

Advent of increased monitoring and new power plants

The nuclear power industry is on the brink of new build construction, with systems monitored by more comprehensive sensor suites than those in legacy plants. This increase in instrumentation will only compound the burden on system engineers who need to monitor for abnormalities and plan for risk-based maintenance.

As with the growth in digital data in general, the growth of data in power plants has increased. This increase

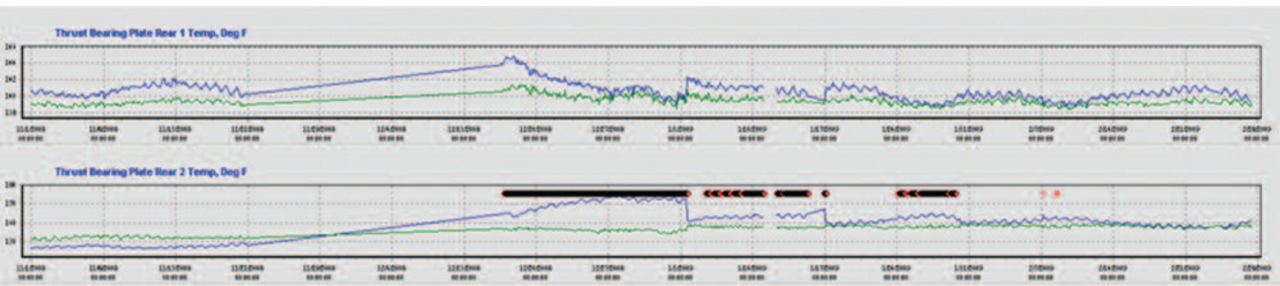

Figure 7: Thrust bearing temperature deviation

means more data must be stored, reviewed, and analyzed. In process control computers, software uses data to control the process parameters. This data is what system engineers trend. Predictive Analytics cuts through the data overload to assist in finding the gem on the ocean floor. The gem is there–just not easy to discriminate with all the refractions going on.

Example- thrust bearing differential temperature

Figure 7 illustrates a turbine thrust bearing differential temperature difference increase above OEM recommendation for normal operation. The temperature difference was between two inactive face temperature probes. The OEM recommendation would have been exceeded and a plant shutdown required without advanced warning. The plant took actions to mitigate the temperature difference. If the differential temperature had continued to rise, the unit would have required a shutdown to resolve the issue. SmartSignal Predictive Analytics provided 18 days early warning of the abnormal rate in temperature increase, which allowed operations, maintenance, and engineers the time to devise and enact a mitigation plan. The advanced notification averted an unnecessary shutdown and potentially a multi-million dollar loss of revenue.

Conclusion

Many deviations are indiscernible by the human eye, especially when the engineer is monitoring hundreds to thousands of sensors within a system. Alerts generally are too late to protect equipment from costly and potentially life threatening damage or failure. The “tried and true” method of relying on actual value hard alerts that typically are set by OEMs and refined by station personnel to protect plant equipment is rapidly being replaced by better technology. Predictive Analytics and TBM use “intelligent trending” to maximize the modeling and monitoring of valuable assets for improved plant reliability and availability.

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